



PHD

Multi-Value Demand Side Response for Low Carbon Networks

Zhao, Chen

Award date:
2017

Awarding institution:
University of Bath

[Link to publication](#)

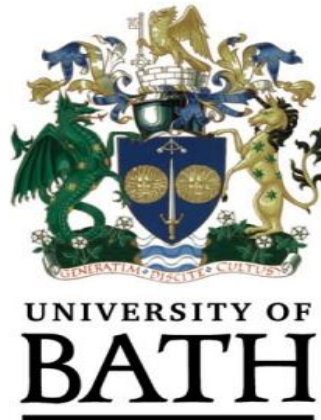
Alternative formats

If you require this document in an alternative format, please contact:
openaccess@bath.ac.uk

Copyright of this thesis rests with the author. Access is subject to the above licence, if given. If no licence is specified above, original content in this thesis is licensed under the terms of the Creative Commons Attribution-NonCommercial 4.0 International (CC BY-NC-ND 4.0) Licence (<https://creativecommons.org/licenses/by-nc-nd/4.0/>). Any third-party copyright material present remains the property of its respective owner(s) and is licensed under its existing terms.

Take down policy

If you consider content within Bath's Research Portal to be in breach of UK law, please contact: openaccess@bath.ac.uk with the details. Your claim will be investigated and, where appropriate, the item will be removed from public view as soon as possible.



Multi-Value Demand Side Response for Low Carbon Networks

By

Chen Zhao

BEng (Hons), SMIEEE

The thesis submitted for the degree of

Doctor of Philosophy

in

The Department of
Electronic and Electrical Engineering
University of Bath

Jan 2017

-COPYRIGHT-

Attention is drawn to the fact that copyright of this thesis rests with its author. A copy of this thesis has been supplied on condition that anyone who consults it is understood to recognise that its copyright rests with the author and they must not copy it or use material from it except as permitted by law or with the consent of the author.

This thesis may be made available for consultation within the University Library and may be photocopied or lent to other libraries for the purposes of consultation.

Signature:.....

Date:.....

Abstract

The increasing penetration of low carbon technologies (LCTs) at customers' premises, such as schools, homes and data centres, presents new opportunities for customers to take an active part in reducing energy and network costs through Demand Side Response (DSR). Meanwhile, the in depth DSR benefits on downstream network architecture, e.g. small and medium demand customers and distribution network operators, could be fully explored. Turning LCT into useful DSR resources to reduce energy volume or shift energy over time requires sophisticated control that can balance interests between customer, network and whole-sale energy market. The limitations of the current DSR control approaches are: 1) complex or inaccurate to formulate the increasingly complicated power flow brought by LCTs; 2) lack of interest balance between customers and network operators; 3) not able to facilitate customers in accessing to both local and central energy market.

This research proposes a range of optimal DSR models in the low carbon environment to introduce three key innovations to overcome the limitation:

- 1) a new problem formulation in DSR optimization model to maximize the customers' DSR return. The proposed formulation generalizes the relationship between power and final energy cost as the simple piecewise functions. The enhanced formulation reduces optimization problem solving complexity and extends modelling capability for conversion efficiency in both local AC and DC low carbon network.
- 2) a new Mixed Integer Linear Programming (MILP) based DSR optimization model that integrates the network demand reduction signal into the constraints of problem formulation to improve network operators' benefit. This research also proposes a novel probability-based quantification method to assess the minimum DSR penetration for concrete network demand reduction considering the demand uncertainty.
- 3) a new MILP based DSR trading model in the market environment of both local and central energy markets. Given different price signals, the proposed model determines the most profitable DSR trading behaviours for DSR providers across central and local energy markets.

Table of Contents

Abstract.....	i
List of Figures.....	v
List of Tables	viii
List of Abbreviations	ix
Chapter 1. Introduction.....	1
1.1 New environment in electrical power system.....	2
1.1.1 Climate change	2
1.1.2 Renewable generation.....	2
1.1.3 Smart Grid	3
1.1.4 Demand side behaviours.....	4
1.2 Research motivation.....	5
1.2.1 Integrating multiple low carbon technologies in DSR.....	6
1.2.2 The effective DSR peak demand reduction in distribution network.....	7
1.2.3 Maximising DSR benefit in new market arrangements.....	8
1.3 Research Objectives and Contributions.....	9
1.4 Thesis Layout.....	11
Chapter 2. Review of Demand Side Response	13
2.1 Introduction	14
2.2 Different DSR types.....	15
2.3 DSR benefits.....	20
2.3.1 Customer benefits	20
2.3.2 Business benefits	21
2.3.3 Market benefits	21
2.4 DSR experience.....	22
2.4.1 UK	22
2.4.2 USA	25
2.4.3 Germany	25
2.4.4 Denmark	26
Chapter 3. New Problem Formulation of Home EMS for Maximum DSR Benefit	28
3.1 Introduction	29
3.2 Overview of EMS system	32
3.3 Optimal HEMS control strategy	33
3.4 Problem formulation.....	35
3.4.1 Building of piecewise function.....	35
A. The piecewise functions of final demand and battery power.....	35
B. The piecewise functions of final energy cost and battery power	38
3.4.2 Conversion of piecewise function into mixed integer model	40
3.5 Demonstration	43
3.5.1 DSR performance of customers.....	44
3.5.2 Sensitivity analysis	46
3.6 Conclusion.....	52
Chapter 4. Improved Problem Formulation for Optimal DSR in Hybrid AC/DC Systems	54
4.1 Introduction	55
4.2 Local hybrid AC/DC network.....	57
4.3 Optimization model of energy management system.....	58
4.3.1 Overview of the Energy Management System	58

4.3.2	Optimization model	59
4.3.3	Model discussion	62
4.4	Problem formulation	62
4.4.1	Building of piecewise function	63
A.	The slopes of the piecewise functions	64
B.	The breakpoints of piecewise functions	65
C.	The value range of piecewise functions	65
D.	Adding price information to piecewise functions	66
4.4.2	Conversion of piecewise function into mixed integer model	67
4.4.3	Process of optimization problem-solving	69
4.4.4	Formulation discussion	71
A.	Reducing complexity of optimization	71
B.	Extending converter efficiency modelling capability	74
C.	Formulation limitation	77
4.5	Demonstration	78
4.5.1	System specification	78
4.5.2	Optimal Results	79
A.	Results of proposed formulation	79
B.	Comparison with single efficiency system	82
C.	Comparison with traditional formulation	84
4.6	Conclusion	85
Chapter 5.	Multi-functional EMS for Maximum Benefit of Network	87
5.1	Introduction	88
5.2	DSR strategy in Sola Bristol Project	91
5.3	Multi-functional EMS model	92
5.3.1	Overview of Multi-functional EMS	92
5.3.2	Simulated optimization model	92
5.4	Benefits quantification method of investment deferral	96
5.5	Test system in trial network	97
5.5.1	Network layout and peak demand	97
5.5.2	Devices parameters	101
5.6	Estimate DSR performance in trial network	102
5.7	Realistic DSR performance in trial network	108
5.7.1	DNO driven DSR strategy trial	108
5.7.2	DSR performance on demand reduction	108
5.7.3	Masked effect of DSR on LV network	111
5.8	Conclusions	116
Chapter 6.	Quantification of DSR Volume for Meaningful Network Impact	118
6.1	Introduction	119
6.2	Methodology	120
6.2.1	Concept of meaningful network demand reduction	121
6.2.2	Algorithm to decide minimum required DSR penetration	121
A.	Algorithm theoretical basis	121
B.	Data-driven Algorithm	123
6.3	Demonstration	125
6.3.1	Minimum required DSR volume	126
6.3.2	Sensitivity analysis	128
6.4	Conclusions	131
Chapter 7.	DSR Management for Local and Central Energy Market	133
7.1	Introduction	134
7.2	Central and local energy market arrangement	137
7.3	Local energy market participants	140

7.4 Optimization model of demand flexibility.....	142
7.5 Problem formulation.....	145
7.6 Demonstration	148
7.6.1 Benefit analysis.....	152
7.6.2 Trading behaviour analysis for different local prices	153
7.6.3 Result discussion for different customer types	162
7.7 Conclusions	167
Chapter 8. Conclusions and future work.....	169
8.1 Conclusion.....	170
8.2 Future work	177
8.2.1 Application of EMS formulation in solving three phase imbalances	177
8.2.2 Improved formulation to cooperate several customers' DSR across network.	177
8.2.3 Improved DSR control for local energy trading	178
Publications	180
Reference	181

List of Figures

Figure 1-1 Electricity generation mix of GB	3
Figure 1-2 Estimate heat pump capacity in the UK	4
Figure 2-1 DSR types classified by customer incentives.....	16
Figure 2-2 Different types of Demand side response and their roles in electric system planning and operation.....	17
Figure 2-3 Example of TOU tariff	19
Figure 2-4 Typical load profile of Economy 7 customer.....	24
Figure 3-1 Overview structure of smart home	32
Figure 3-2 Energy management system.....	33
Figure 3-3 Piecewise function when demand is larger than PV output.....	37
Figure 3-4 Piecewise function when demand is smaller than PV output	37
Figure 3-5 Piecewise function of scenario 1	38
Figure 3-6 Piecewise function of scenario 2.....	39
Figure 3-7 Piecewise function of scenario 3.....	39
Figure 3-8 Piecewise function of scenario 4.....	40
Figure 3-9 Customer demand and PV output	44
Figure 3-10 Battery SOC	45
Figure 3-11 Demand change after DSR.....	46
Figure 3-12 Load profiles of three types of electric heat customers.....	47
Figure 3-13 Battery SOC of four types of load profiles.....	47
Figure 3-14 Demand change of overnight heating customer.....	48
Figure 3-15 Demand change of daytime heating customer	48
Figure 3-16 Demand change of evening heating customer	49
Figure 3-17 Battery SOC with different battery charge rates	50
Figure 3-18 Battery SOC with different conversion efficiencies.....	52
Figure 4-1 Overview structure of a local hybrid AC/DC system	58
Figure 4-2 Energy management system.....	59
Figure 4-3 Demand representation in the hybrid AC/DC system.....	64
Figure 4-4 Converter efficiency.....	65
Figure 4-5 Piecewise function of energy cost and DC power	66
Figure 4-6 Flowchart of optimization problem-solving.....	70
Figure 4-7 Demand representation with constant converter efficiency	72
Figure 4-8 Converter efficiency.....	75
Figure 4-9 Relationship between efficiency and price ratio	77
Figure 4-10 TOU tariffs	77
Figure 4-11 School AC demand	79
Figure 4-12 PV output	79
Figure 4-13 Winter term weekday SOC	80
Figure 4-14 Winter term weekday demand	80
Figure 4-15 Network demand	81
Figure 4-16 Winter holiday weekday SOC.....	82
Figure 4-17 Winter holiday weekday AC-to-DC power.....	83
Figure 5-1 Overview of multi-functional EMS	92
Figure 5-2 The piecewise function representation with network request.....	94
Figure 5-3 Flowchart of optimization problem solving with network request	95
Figure 5-4 Tested network layout	97

Figure 5-5 Peak demand of Feeder 1	99
Figure 5-6 Peak demand of Feeder 2	99
Figure 5-7 Peak demand of network	100
Figure 5-8 Load profiles of Feeder 1	100
Figure 5-9 Load profiles of Feeder 2	101
Figure 5-10 Load profiles of substation	101
Figure 5-11 Typical load profile and PV output	103
Figure 5-12 TOU tariff	103
Figure 5-13 Battery SOC with noon time network request	104
Figure 5-14 Battery SOC with evening time network request	105
Figure 5-15 Customer demand change without network request	105
Figure 5-16 Customer demand change with noon time network request	106
Figure 5-17 Customer Demand change with evening time network request	107
Figure 5-18 Household load profiles comparison	109
Figure 5-19 Network and household load profiles comparisons	110
Figure 5-20 Network demand uncertainty in tested network	112
Figure 5-21 Feeder demand uncertainty in the tested network	112
Figure 5-22 Demand distribution during peak time of tested network in April	113
Figure 5-23 Cumulative distribution of demand in peak time of tested network in April	113
Figure 5-24 Open bounded interval for peak demand sampling values	114
Figure 5-25 Peak demand sampling values during a period	114
Figure 5-26 Visible effect of demand reduction	115
Figure 5-27 Masked effect of demand reduction	115
Figure 6-1 Probability that DSR can reduce network demand given the knowledge of a demand sample A_i	122
Figure 6-2 Flow diagram of data drive algorithm	125
Figure 6-3 Substation layout	126
Figure 6-4 Demand distribution during peak time	126
Figure 6-5 Minimum required DSR volume at different confidence levels	127
Figure 6-6 Minimum required DSR volume of different deltas	128
Figure 6-7 Relationship of minimum required DSR volume reductions and deltas ..	129
Figure 6-8 Minimum required DSR volume of different months	130
Figure 6-9 Peak demand distributions of different months	130
Figure 6-10 Minimum required DSR volume of different locations	131
Figure 6-11 Peak demand distributions of different locations	131
Figure 7-1 Market participant connections under “one bill mode”	137
Figure 7-2 Market participant connections under “two bill mode”	138
Figure 7-3 New market structure	139
Figure 7-4 Overview structure of the EMS system	146
Figure 7-5 Central TOU price	149
Figure 7-6 Local market prices	150
Figure 7-7 Domestic customer demand and PV output	151
Figure 7-8 School customer demand and PV output	151
Figure 7-9 Trading prices in base case	154
Figure 7-10 Trading energy in base case	154
Figure 7-11 Trading prices in case 2	155
Figure 7-12 Trading energy in case 2	155
Figure 7-13 Trading prices in case 1	156
Figure 7-14 Trading energy in case 1	157

Figure 7-15 Trading prices in case 4.....	158
Figure 7-16 Trading energy in case 4	158
Figure 7-17 Trading prices in case 3.....	159
Figure 7-18 Trading energy in case 3	159
Figure 7-19 Trading prices in case 5.....	160
Figure 7-20 Trading energy in case 5	160
Figure 7-21 Battery SOC's comparison in case 5	163
Figure 7-22 AC-DC power exchange comparison in case 5.....	163
Figure 7-23 Trading energy of school in case 5	164
Figure 7-24 Trading energy of domestic home in case 5.....	164
Figure 7-25 Battery SOC's comparison in case 2	165
Figure 7-26 AC-DC power exchange comparison in case 2.....	166
Figure 7-27 Trading energy of school in case 2	166
Figure 7-28 Trading energy of domestic home in case 2.....	166

List of Tables

Table 2-1 Classification of DSR	Error! Bookmark not defined.
Table 2-2 DSR integration strategies of National Grid	23
Table 3-1 Piecewise function scenarios	36
Table 3-2 Battery parameters	43
Table 3-3 TOU tariffs	44
Table 3-4 Bill savings of different types of customers	49
Table 3-5 Bill savings with different battery charge rates	51
Table 3-6 Bill savings with different conversion efficiencies	52
Table 4-1 Variable and constraints number comparison	72
Table 4-2 Solution space comparison	74
Table 4-3 Battery and converter parameters	79
Table 4-4 Benefit quantification	81
Table 4-5 Benefit comparison in demand shifting	83
Table 4-6 Formulation comparison	85
Table 5-1 Household connection points	97
Table 5-2 Measured network peak demand	98
Table 5-3 Battery parameters	102
Table 5-4 Customer bill savings with network request	103
Table 5-5 Network investment deferral with 42% network utilization	107
Table 5-6 Network investment deferral with 85% network utilization	108
Table 5-7 DNO-driven DSR strategy	108
Table 5-8 Quantification of percentage of DSR effect been masked at feeder 0021 in network demand reduction trial	110
Table 7-1 Scenarios with different binary coefficients	146
Table 7-2 Devices parameters	152
Table 7-3 Cases with different prices	152
Table 7-4 Profits in different cases	153
Table 7-5 Traded energy buying and selling prices	160

List of Abbreviations

CPP	Critical Peak Pricing
DECC	Department of Energy & Climate Change
DER	Distributed energy resources
DG	Distributed generation
DNO	Distribution network operator
DSO	Distribution system operator
DSR	Demand Side Response
ED-CPP	Extreme Day CPP
EDP	Extreme Day Pricing
EMS	Energy management system
ESCOs	Energy service companies
EU	European Union
EVs	Electric vehicles
FFR	Firm Frequency Response
FSL	Firm service level
GB	Great Britain
HEMS	Home EMS
I&C	Industrial and Commercial
IBP	Incentive-Based Programs
ISO	Independent system operators
LCTs	Low carbon technologies
LED	Light-emitting diode
Micro-CHP	Micro-Combined Heat and Power
MILP	Mixed integer linear programming
Ofgem	Office of Gas and Electricity Markets
OPF	Optimal power flow
PBP	Price Based Programs
PSO	Particle swarm optimization
RHI	Renewable Heat Incentive
RTP	Real Time Pricing
SEDC	Smart Energy Demand Coalition
SOC	State of charge
STOR	Short Term Operating Reserve
TOU	Time of Use
TSO	Transmission system operator

Chapter 1. **Introduction**

1.1 New environment in electrical power system

1.1.1 Climate change

In response to climate change, many countries have set targets and policies to reduce greenhouse gas emissions. In 1997, 39 developed countries and the European Union (EU) signed the “Kyoto Protocol” aiming to make commitment on greenhouse gas emission [1]. EU, particularly, sets ambitious to reduce 20% of greenhouse emission by 2020 compared with the 1990 levels [2]. To play a part in reducing global emission, the UK government published ‘Climate Change Act 2008’[3], aiming to cut the UK emissions by 34% by 2020 and at least 80% by 2050. Further ambition is to bind the emission reductions to growth of distribution generate and electrification of heating and transportation [3]. As a consequence, electricity generation, transport and consumption will change significantly from the way they were yesterday.

1.1.2 Renewable generation

At the same time, the electricity system is changing from large-scale conventional fossil fuel dominated generation mix to intermittent renewable generation in the Great Britain (GB) as shown in figure 1-1 [4]. Over the past ten years, 2006 to 2016, the Wind and Solar generation increased from 1.09TWh/quarter to 12.9TWh/quarter. Also, the coal generations are largely reduced from 47.56TWh/quarter to 13.89TWh/quarter.

Electricity generation mix by quarter and fuel source (GB)

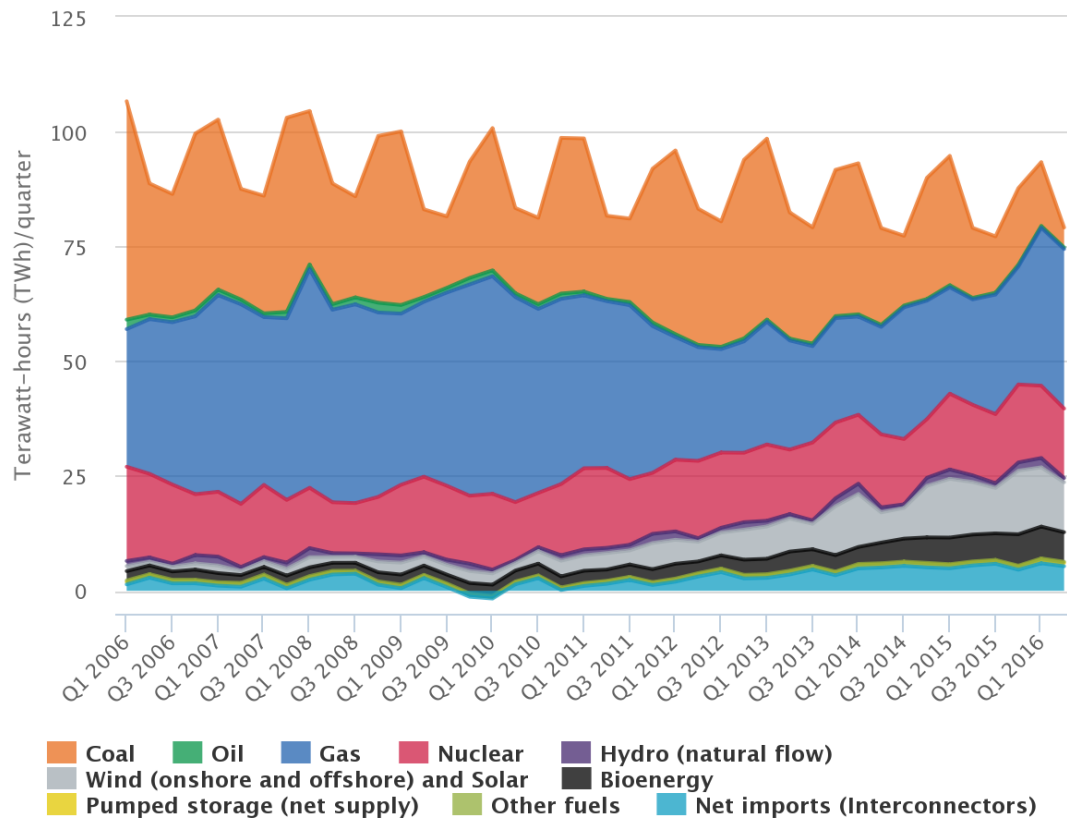


Figure 1-1 Electricity generation mix of GB

1.1.3 Smart Grid

Electricity transmission and distribution system have undergone great revolution with the promotion of “Smart Grid” [5, 6]. Smart Grid aims to provide intelligent, efficient and economical solutions for reliable and safe power supply, minimal energy cost and low carbon electricity system. In detail, in a Smart Grid context, there will be increasing use of digital information and control technology; dynamic optimization of grid operation and resources; deployment and integration of distributed resources, incorporation of demand side response; and real-time monitoring, communication technologies [7, 8]. GB has made significant progress in deploying smart grids with respect to the investment in smart grid research and demonstration projects [9]. The Office of Gas and Electricity Markets (Ofgem) proposed a new RIIO Price Control [10, 11] model facilitating the network innovation and creating £500 million Low Carbon Networks Fund [12] to encourage network company innovation projects that test and trail new smart grid technologies and solutions. Additionally, GB has also begun the

nationwide rollout of smart meters [13, 14] to improving network management and facilitating demand shifting.

1.1.4 Demand side behaviours

Meanwhile, consumption behaviours have significantly changed because of the large integration of low carbon technologies (LCTs) at the demand side. In the UK, small-scale embedded generators, electrification of heating and transport have been paid increasing attentions. The domestic PV installation in the UK has increased between 375-900MW each year since 2011 after the introduction of Feed-in Tariffs [15] in April 2010. Until the end of 2015, there were 740,077 sites of the small-scale PV installations[16]. On the heat side, by 2014, the renewable heating represents 2% of the heating system in the UK. However, the government incentive policies, Domestic Renewable Heat Incentive (RHI) [17] implemented by April 2014 have boosted the adoption rate in the UK. It is estimated the total heat pump capacity in the UK will rise to 5.4-5.6GW by 2020 [18] and the site number will exponentially increase since 2020 [9] as shown in the figure 1-2. On the transport side, the demand for electric vehicles has a remarkable surge: the registered plug-in cars increased from 3,500 in 2013 to more than 80,000 by Dec 2016 in the UK [19].

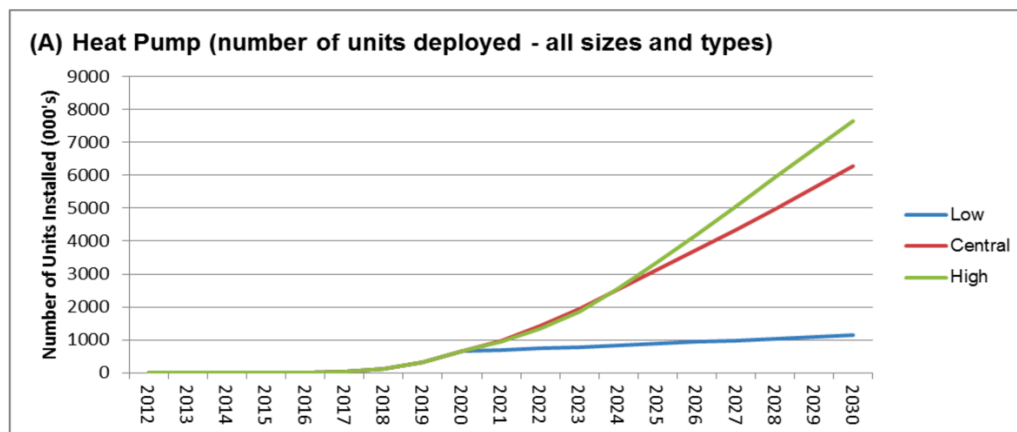


Figure 1-2 Estimate heat pump capacity in the UK

These low carbon technologies integrated on demand side and the rollout of smart metering system pose substantial opportunities for customers to participate in the electricity industry. The customers could not only shift demand manually according to the given signals, but also rely on the smart meter, low carbon technologies and remote

or on-site control system to change the demand behaviour in the power system.

The Demand Side Response (DSR), as an active demand reduction or demand shifting over time by customer, will bring benefit to all the participants in the electricity system: 1) avoiding or deferring capacity cost for generators; 2) improving network operation and deferring network infrastructure investment for network operators; 3) bringing financial benefit for participated customers. Over the past years, the role of DSR has been highlighted due to its significant impact on electricity industry. Ofgem has assessed the impact of DSR [20] in the UK that if customers shift 5% to 10% of their electricity use from peak to trough time, it would bring up to £1.7 million daily wholesale cost savings; up to £536 million annual avoided capital costs for new generation; and up to £28 million annual avoided capital costs for networks. Therefore, wide ranges of researches and projects have been carried out to promote the development of DSR.

1.2 Research motivation

The DSR offered by large-demand customers have been extensively explored in the wholesale market, capacity market and balancing/ancillary market around the world [21-25]. However, the DSR from small and medium demand customers and its contributions to downstream network structure, including customers themselves, distribution network operators and regional energy market are almost untapped. The limited implemented DSR schemes involving small and medium demand customers are direct load control or interruptible/curtailable schemes and Time of Use (TOU) tariffs, such as Economy 7 [26] in the UK. The traditional controllable loads are air conditioner, washing machine, dish washer and heating

However, increasing penetration of low carbon technologies (LCTs), particularly small scale embedded generators, such as PV, energy storage, and heat pumps, are likely to be connected at distribution network and customer properties. These technologies impose new challenges and opportunities in DSR, because they are not only changing the original distribution network operation philosophy, but also offering more demand flexibility to end users as well as creating market opportunities.

The motivations of this PhD research are mainly from three aspects:

1.2.1 Integrating multiple low carbon technologies in DSR

Over recent years, the low carbon technologies, especially renewable generation and energy storage have been advocated by the UK government. The domestic PV installation in the UK has increased between 375-900MW each year since 2011 and Department of Business, Energy & Industrial Strategy has published that the PV capacity nearly reach 12GW by 2017 [27, 28]. At the same time, the UK government has issued that the energy storage is one of the eight great technologies that UK can become a global leader [29]. Department of Energy & Climate Change (DECC) forecasted that energy storage could result in savings of £2.4 billion per year in 2030 and have committed more than £80 million to energy storage research [30]. It is expected that the small-scale battery storage in domestic and commercial customers' place would rise from 400MWh now to 760GWh in 2040. The combination of battery storage and solar PV is promising future for the UK [30] and could play a significant role in DSR. Therefore, the biggest challenge lies in how to optimally integrate these low carbon technologies into DSR and maximize the benefit for the system architecture with the acceptance of the owner of the equipment. An effective and simple energy management strategy needs to be developed.

Additionally, in the near future, the increasing in-home DC LCTs would take active role in demand side response. Building the hybrid AC/DC system effectively reduces AC/DC conversion loss in the system operation. In the hybrid AC/DC system, a separate DC bus is built to connect DC generation and load. However, in the hybrid AC/DC system, there can be increased energy components and power flow in any directions between DC generation, DC load, main grid (AC generation) and AC load. Besides, the power conversion efficiency differs with whether the power is exchanged between AC and DC system or transferred within the AC or within the DC system. As a result, in order to optimize the energy flow in the hybrid AC/DC system, more sophisticated energy management system is indispensable. The increased components bring significantly increased variables/constraints to represent exchange power between battery, local DC bus, local AC bus and main grid in the energy management model.

Majority of the previous DSR models either have large solution space that is complex to solve or oversimplify the optimization model for faster solution. The previous DSR control strategies are often designed on component level, which enumerate power exchange between components. It would exacerbate the calculation burden and increase the difficulty in finding the optimal solution. Additionally, the component level problem formulation could only assign constant AC/DC conversion efficiency within the model. The simplified constant system efficiency is inaccurate to represent the realistic EMS model and thus reduce the customer benefits. Therefore, a more efficient and accurate DSR control model for increasing DC low carbon technologies should be designed to maximize the customer DSR benefits.

1.2.2 The effective DSR peak demand reduction in distribution network

In the future, as electricity demand, network variable and distributed generation increase, distribution network operator expects more active role in network operation as transmission system operator (TSO). Therefore, Distribution Network Operator (DNO) is moving to Distribution system operator (DSO). This may include activities to ensure demand and supply on the network is balanced or decreasing demand through DSR [20]. One of the foreseeable situations certainly will be faced by distribution network operators is the increasing peak demand on LV network brought by low carbon technologies, such as electric vehicles (EVs) and heat pumps. It is estimated that electrification of transport and heating could add an additional 5-15% electricity demand by 2030 [31]. Currently, without the smart control of charging, the EV charging has been proved to contribute a rise in domestic peak demand [32]. A heat pump would double the electricity use of an average household in existing buildings in the winter[32, 33]. On the LV network, majority of the customers are small and medium demand customers. Therefore, DSR from small and medium demand customers that could response to the network operator's requirements is crucial to reduce the peak demand on the network and bring benefits that could defer network infrastructure investment.

Majority of the previous DSR model designed for downstream network architecture is either for minimum electricity cost for customers or minimum peak-to-average ratio for network operators. In their models, the benefit for the other stakeholder, (network

operator or customer) is always achieved as a by-product in the optimization. For example, in the studies to minimum electricity cost, network peak demand reduction is achieved by synchronized high price and network peak demand. Therefore, a multi-functional energy management that could facilitate both network operators and customers is necessary.

Additionally, majority of the previous researches estimates the network demand reduction effect from DSR by cumulating simulated demand from households [34-36]. In these researches, the network demand is assumed to be deterministic so that the demand reduction on network can be assessed easily by summing up the individual DSR contributions of each engaged households. However, there is very little evidence to suggest realistic DSR can perform as expected. Therefore a thorough field investigation and a proper benefit evaluation which can tell how much exactly demand reduction that DSR could bring to realistic network peak is imperative.

1.2.3 Maximising DSR benefit in new market arrangements

There is increased unbalanced demand on the distribution network introduced by LCTs. The household renewable generations and large controllable loads are dispersed in difference places on the distribution network that would introduce thermal and voltage violations. Apart from technical solutions, commercial tools and market mechanisms are emerging to solve the problems.

Traditionally, the electricity is generated from large scale generation plants, delivered from transmission to the distribution network and then to customers in a unidirectional way. The existing energy market of UK and some EU countries consists of five main participants: generators, transmission system operators (TSOs), distribution system operators (DSOs), suppliers (retailers) and customers. However, with the increasing number of LCTs, especially distributed energy resources (DER) connected to the distribution network and premises of customers, customers with flexible DER should change the original role to prosumers and gain the capability to access and impact the energy market. Additionally, there will be new market participants, such as aggregator and energy service companies (ESCOs) in the energy market to facilitate DER operations. The local energy market, with different types of DSR as commodities, would be emerged to facilitate the traditional energy market to

mitigate the adverse impact brought by DER and maximize the market participants' benefit. In the meantime, the multiple energy markets bring abundant or excessive market information and choices to the customers.

Currently, little research has investigated the value of DSR, as a commodity, to local market formulations. And there is little attention to the optimal DSR trading behaviours for individual customer within the local energy market and multiple energy markets environment. Therefore, a study to investigate the most feasible and profitable DSR trading management for customers in the promising new market arrangement is indispensable.

1.3 Research Objectives and Contributions

This research proposes the improved demand side response approaches and maximizes the DSR benefit for downstream network architecture with three challenges brought by low carbon technologies: 1) Complex power flow brought by increased renewable generations and controllable components; 2) Different interests for customer and network operators; and 3) Emerging new market arrangements and booming market choices and information. The major objectives and the main contributions are as followed:

- To design an efficient DSR model to solve complex power flow with the integration of low carbon technologies and maximize the customer benefit in DSR since the customer benefit is the strongest factor that motivates the adoption of DSR.

In doing so, firstly, a novel piecewise function formulation to optimize the battery charging and discharging behavior for DSR is proposed. The formulation simplifies the mathematical representation in the DSR model with renewable generation and energy storage as piecewise functions. It transfers the information of possible power flow, price, battery capacity and battery and AC/DC conversion efficiency into the relationship between battery energy and final energy cost. The relationship then is represented by piecewise functions and solved by mixed integer linear programming (MILP).

Additionally, an extended new piecewise function problem formulation for optimizing DSR strategy within the hybrid AC/DC system is developed. Instead of building the formulation from a component level, which enumerate power exchange between components, such as battery, DC/AC local system and main grid, the proposed formulation is built at the whole system level such that all power transfers between AC/DC or DC/AC are reflected in the AC power drawn from the main grid. As a result, it significantly reduces complexity in optimization by substantially reducing the number of variables/constraints and searching space. Also, the proposed formulation extends modelling capability for converter efficiency by building in the power-related converting efficiency.

- To integrate both network and customer interests in the optimal DSR model and to quantify realistic network peak reduction impact from DSR. The enhanced model should facilitate both network investment savings and customer electricity bill savings.

In doing so, a new DSR optimization model for multi-functional energy management system (EMS) is developed. The proposed optimization model is designed for the shared battery DSR system, which will respond to network demand reduction requirement as well as maximize the customer electricity bill savings. The optimization model is solved by proposed piecewise function formulation and MILP. The research for the first time: assesses the household DSR performance on network demand reduction with practical evidence.

Additionally, a novel probability-based data-driven algorithm is proposed to quantify the minimum required DSR penetration for concrete network demand reduction. The quantification method calculates the probability guarantees on meaningful network demand reduction. The research for the first time quantifies the minimum domestic DSR volume required to bring certain degree of concrete network demand reduction in the presence of inherent demand uncertainties in LV networks.

- To investigate the DSR models in the new market arrangement environment and maximize DSR benefits within multiple market choices. The proposed optimization model should also facilitate development and implementation of

various on-going local energy market concepts.

In doing so, a novel MILP based DSR optimization model is developed. The proposed energy management system could derive the optimal trading opportunities for customers from both central and local energy market based on the price signals from multiple markets. Additionally, a local energy market formulation with DSR as a commodity is developed. In essence, this part of the work for the first time investigates the feasibility and profitability of DSR trading behaviours in local energy market for different customers, with different adopted low carbon technologies and with different load types.

1.4 Thesis Layout

The rest of the thesis is organized as follows:

Chapter 2 provides a comprehensive literature review of DSR. In particular, the DSR categories, including their targeting customer types; DSR benefits to customers, business and market level; and DSR experience in GB and worldwide are investigated.

Chapter 3 proposes a piecewise function problem formulation to optimize the battery operation for maximum customer electricity bill savings. It simplifies the optimization process by transferring all of the information on possible power flow, price, battery capacity and battery and AC/DC conversion efficiency into the relationship between battery energy and final energy cost. The formulation is then solved by mixed integer linear programming.

Chapter 4 follows previous chapter to develop the optimal DSR strategy with maximum customer benefits. It proposes an improved piecewise function formulation in optimal EMS to model the power flow in hybrid AC/DC network. The proposed formulation is built at the whole system level such that all power transfers between AC/DC or DC/AC systems are reflected in the AC power drawn from the main grid. Additionally, the power-related conversion efficiency is integrated into the formulation.

Chapter 5 extends the previous designed EMS with network operators' demand

reduction requirement, which aims to maximize both network operators' and customers' benefits. A multi-functional EMS is designed for the shared battery DSR system between customers and network operators. The DSR simulation results and realistic results on network demand reduction are discussed. This chapter for the first time provides how the realistic DSR performance on network demand reduction and how the results are different from what are expected.

Chapter 6 develops a probability-based algorithm to quantify the minimum required DSR penetration rate for meaningful network demand reduction. Given the uncertainty in LV network demand, the chapter firstly define the meaning network demand reduction. Then, the “divide-and-conquer” strategy is adopted to find the minimum required DSR penetration and with reduced calculation complexity. The results provide a guide for network operators on how much DSR would be required for concrete network benefits.

Chapter 7 designs an innovative EMS for optimal trading opportunities for individual customer within central and local energy markets. The different DSR trading behaviours for different customers with different adopted low carbon technologies and with different load types are discussed. The formed local trading structure and consequent results would facilitate building on-going local energy market concepts and designing feasible and profitable local energy market formulations.

Chapter 8 summarizes the major contributions of the work and the key findings from the research. The potential research topics in future work is also provided.

Chapter 2. **Review of Demand Side Response**

2.1 Introduction

Traditionally, the philosophy of operating the electric power system is to let supply match demand at all times. Power stations have to change the amount of electricity generation in real time and network operators need to invest on the transmission and distribution network capacity in order to guarantee the electricity can be transported to end user.

However, with the development of control and communication, an additional philosophy is applicable: to actively change the demand to reduce the pressure on power generation, transmission and distribution, and increase the whole system efficiency. The concept of “Demand Side Response” is used to describe the new philosophy.

Demand side response refers to actions taken by consumers to change the amount of electricity they take off the grid at particular times in response to a signal [20]. It can help generators and network operators to reduce demand peaks and fill in the troughs, especially at times when power is more abundant, affordable and clean [21].

Traditionally, the DSR is always achieved by changing the original industry/commercial/household electricity behaviour, i.e. changing the operation of machines and home appliances. The behaviour change of the customers could be divided into two types. Firstly, the electricity demand is reduced during the peak demand/price time by customers/utilities without changing the consumption pattern during other periods. The second type is to shift electricity usage to off-peak time manually or by changing the setting of machines/home appliances. An example would be to shift the washing machine and dish washer operation time to late night or other off-peak period. However, the traditional DSR is always in company with temporary loss of comfort for domestic customers. For example, the customers/utilities would turn-off or change the temperature of air-conditioner or electric heating to reduce the electricity demand during the peak time. Additionally, the DSR is not always feasible for certain commercial and industrial customers, since in most case their demands are indispensable and fixed.

In the low carbon environment, the increasing number of LCTs, such as distributed

generation and energy storage [37-39] will naturally change the load profiles of customers seen from network side. It could involve little change in customers' daily behavior and therefore customers will not sacrifice any comfort. However, the outcome of LCTs connection is not always solving the problems on networks and generation sides. For example, the output of renewable generation will not mitigate the peak demand of the system during majority of the time; the controllable distributed generation, such as Micro-Combined Heat and Power (Micro-CHP) [40, 41], will not always operate during the electricity peak period; and the energy storage could not charge and discharge intelligently based on the system peak and off-peak demand. Therefore, DSR involving LCTs would require additional technical solutions to manage additional generation or demand in order to achieve effective peak reduction/shifting. How to manage the additional generation or demand brought by LCTs could become a new challenge in DSR.

2.2 Different DSR types

DSR can be divided into two general types: Incentive-Based Programs (IBP) and Price Based Programs (PBP) as shown in figure2-1 [42, 43]. In some literatures, the two types are called “explicit” and “implicit” Demand Side Response [44]. In IBP schemes (Explicit DSR), customer will directly receive payment that are separate from, or additional to, their retail electricity rate from utility companies [45] and there will be commercial agreement between customers and utility companies. While in PBP schemes (Implicit DSR), customer will save the electricity cost if they reasonably allocate electricity demand during the day according to the smart tariff, i.e. non-flat tariff.

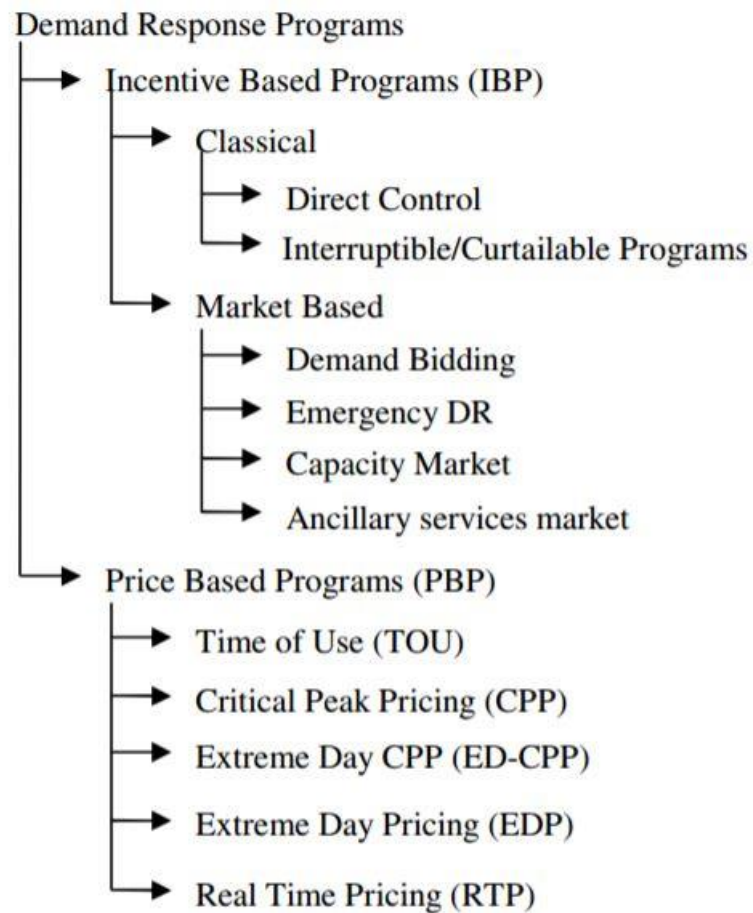


Figure 2-1 DSR types classified by customer incentives

In detail, the IBP schemes are differentiated by load commitment planning timescales, as shown in figure 2-2, load reduction purposes, payment methods, and applied customers.

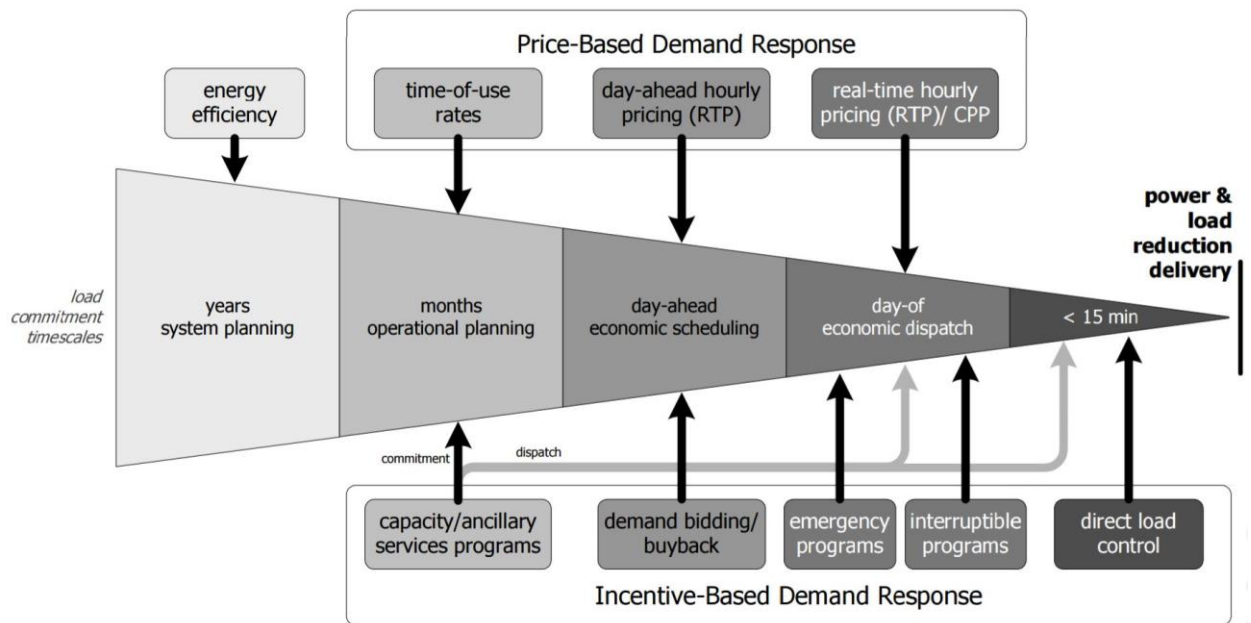


Figure 2-2 Different types of Demand side response and their roles in electric system planning and operation

- Direct load control

In Direct load control, utilities will have the rights to remotely control customers' appliances, such as air conditioner and water heater on a short notice under the agreement. This type of the DSR is often planned within 15mins of the load reduction implemented and operated as the final flexible load control. The participated customers will receive participation payment, usually in the form of a bill credit. This type of the DSR is primarily offered to domestic and small commercial customers.

- Interruptible/curtailable Services

In Interruptible/curtailable Services, customers will need to reduce the load, typically to a pre-specified firm service level (FSL), during system contingencies according to the agreement. The load reduction will be planned based on the economic dispatch on the day. The participated customers will receive a discounted electricity rate or bill credit. However, if the customer fails to reduce the load based on the agreement and notice, penalties will be incurred as a very high electricity rate during contingency events or be removed from the program. Interruptible/curtailable Services are primarily offered to large industrial or commercial customers.

- Emergency Demand Response Programs

Just as its name implies, Emergency Demand Response Programs work as a short decided (on the day), emergent load reduction programs during the reliability triggered events. It will ask the potential customers to reduce demand according to their capability to relief the system pressure. Customers will be provided with an incentive payment according to the measured load reductions and are not necessary received penalties if the load reduction is not implemented.

- Demand Bidding/Buyback Programs

This type of DSR encourages large demand customers 1) to bid in wholesale electricity market day-ahead and offer to provide load reductions at a price at which they are willing to be curtailed; or 2) to decide how much reduction they willing to offer given a utility-posted price. If the bid is accepted, the customer must reduce the load as agreed, otherwise, they will face a penalty.

- Capacity Market Programs

This type of DSR contributes to capacity market which is planned months ahead. Capacity market is to ensure security of electricity supply by providing a payment for reliable sources of capacity. The Capacity Market DSR Programs can commit to providing pre-specified load reductions as a form of reliable capacity during the planning and bid stage of capacity market. The customers typically receive day-of notice of events. The up-front reservation payments, determined by capacity market prices (auction clearing price), and/or additional energy payments for reduction during the events will be paid to the customers. Capacity Market Programs typically have significant penalties to customers do not implement the load reduction. This type of DSR is suitable for large demand customers.

- Ancillary Service Market Programs

Ancillary Service Market programs means customers bid load curtailment in balancing market as operating reserves and frequency response. In the UK, the equivalent is Balancing Market. If the bid is accepted, the customers are paid the market price for committing as a standby. If the load curtailments are needed, they are called

by the system operator and may be paid the spot market energy price.

The PBP schemes are differentiated by different smart tariffs. In detail, there are Time of Use (TOU) tariff, Real Time Pricing (RTP), Critical Peak Pricing (CPP), Extreme Day CPP (ED-CPP) and Extreme Day Pricing (EDP). The prices are different during different time period in order to encourage customers flatten the demand curve.

- Time of Use (TOU) tariff

Time of Use tariff provides pre-defined different unit prices during different period of time as shown in the example in figure 2-3. TOU tariff intends to reflect the average cost of generating and delivering power during those time periods. TOU tariff rates often vary by time of the day and by season. The rates are typically pre-determined for months or years. One of the simple examples of TOU is the Economy 7/Economy 10 applied in the UK [46], which just has day and night splits. Nowadays, TOU tariff is the most common PBP schemes: 20% customers [16] are using Economy 7 and Economy 10 in the UK and many electricity supply companies provide TOU schemes to customers worldwide.

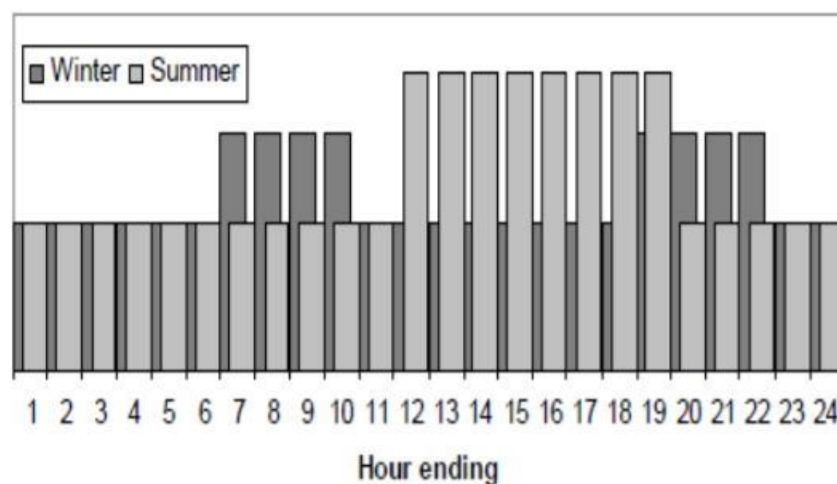


Figure 2-3 Example of TOU tariff

- Critical Peak Pricing (CPP)

Critical Peak Pricing is an improved TOU tariff [47] that includes a pre-specified extremely high rate for the critical peak period. CPP prices are used during

contingencies or high wholesale electricity prices for limited hours per year or number of days. The high unit price and period are notified to customers at least on day ahead. During non-CPP periods, customers typically receive a price discount. CPP is not yet common and been tested in pilots.

- Real Time Pricing (RTP)

Real Time Pricing is to directly reflect the dynamic wholesale electricity price variations. The prices of the tariff typically vary every hour or half hour. RTP customers are informed about the rates day-ahead or hour-ahead. The DSR scheme based on RTP will be closely linked to system conditions and energy market performance and therefore could be the most direct and efficiency DSR programs [42]. However, the demand shifting requires frequent attention to the price variation [48]. Currently, RTP is mostly applied to commercial and industrial customers with real time meters.

2.3 DSR benefits

The DSR potential benefits can be concluded to three general categories: direct customer benefits, business benefits and market benefits. However, the three types of DSR benefits will all eventually bring benefit to all the customers by increasing the whole system performance, including reduce the wholesale energy price, defer infrastructure enforcements, increase network operation reliability and increase the market efficiencies.

2.3.1 Customer benefits

Firstly, the customers participating in DSR could receive financial benefits directly. The amount of the financial benefits depends on the technologies adopted and the demand shifting capability and flexibility. If customers take part in IBP schemes and reduce the load according to the agreement, they could expect direct payments or electricity rate discount. If they use the PBP schemes and shift demand from high price hours to low price hours, they could receive the electricity bill savings based on the amount of demand shifting.

The other customers could also directly benefit from implemented DSR from DSR

participants. The overall electricity price reduction is expected from marginal supply cost and wholesale energy cost reduction. The marginal supply cost and the wholesale market clearing price will reduce because of the reduction of demand from expensive electricity generations. If the links between wholesale energy costs and electricity rates are built, the bill savings to all the customers would be achieved.

2.3.2 Business benefits

The DSR business benefits are benefits to electricity utility companies, which could be divided to financial benefit and operational benefit. DSR produces business benefits that are realized by a group of consumers. The financial benefits are to avoid or defer the investment of additional generation, transmission and distribution infrastructure by reducing the system peak demand. Because the electricity industry is capital intensive, avoided infrastructure investment is a significant source of savings. The operational benefits refer to it is easier for network operators to increase the power quality and reduce the probability and severity of outages and electricity interruption. The operators will have more options and resources to maintain the system reliability [42]. Especially, the DSR types of Capacity Market Programs and Ancillary Service Market Programs are design to facilitate network operators [49].

2.3.3 Market benefits

DSR is an important force to improve market arrangements and increase market efficiency. DSR participants have more choices and also provide more choices to other customers in the energy market. As a consequence, more market participants, such as Energy Service Companies (ESCOs) [50], emerge in the energy market to manage DSR. Additionally, new markets [51, 52], such as local energy market, emerge to compete with traditional market. Customers could trade distributed energy resources (DER) in the local energy market. The renewable energy and cheap shifted energy by the storage could make the energy price in the local energy market quite competitive compared with that in the traditional market. The induced new market roles and structures will enhance the original market arrangement, which could efficiently bring lower energy cost, reduce uncertainties brought by renewable generations, and further increase low carbon technology integration and reduce carbon emission.

The different benefit aspects derive from multi value stream of DSR. This research proposes several approaches to facilitate customers, business and market to gain increased benefit from DSR.

2.4 DSR experience

2.4.1 UK

The electricity industry in the UK has paid lots of attention to system flexibility [53, 54], which indicates that “modifying generation and/or consumption patterns in reaction to an external signal (such as a change in price) to provide a service within the energy system”. In addition to the traditional flexibility on “supply side”, more emphasis is on the “demand side”. As a consequence, comprehensive investigations have been implemented on the DSR, for example, the policy environment, barriers and potential, role of aggregators in the market, the potential of energy storage and DSR integration in capacity and balancing market etc.. In this section, only a part of latest typical DSR investigations and projects are discussed.

The UK Department of Energy and Climate Change (DECC) has initialized a DSR project D3 in 2014 [49, 55], which indicates Demand reduction, Demand response, and Distributed energy. One of the reports produced is to examine how demand side measures are considered in the policy development process across government. Current policies are analysed and ten recommendations are proposed in the report, including that government needs to set out more coherent plan to reduce the risk that benefits and opportunities are missed; DECC should consider setting an energy demand management target for the UK; government and industry should work together to identify the market barriers for demand side activity as the energy market accommodates greater levels of DSR; and local area decentralised energy plans should be developed etc. [55].

An Industrial and Commercial (I&C) demand side response (DSR) barriers and potential analysis [56] is conducted by Ofgem in 2016, who is the regulator of GB electricity system. More than 100 I&C consumers and 80 procurers (suppliers, aggregators, and network operators) took part in the survey. The results show that until

2016 the current demand reduction provided by I&C customers is about 350MW. Over 400MW of technically and commercially viable additional demand reduction is potentially available. It is estimated that there is 3GW demand reduction potential and 1.9GW demand increasing potential across the whole GB. For I&C customers, the barriers are located both in business and financial aspects. From business point of view, the customers concern the conflict between their business and DSR requirement and they have limited understanding of DSR value. From financial point of view, the DSR non-providers consider there is no financial incentive that could lead them to offering DSR. The predominate barrier for procurers in GB comes from regulatory and commercial aspects.

National Grid, who is the system operator in the UK, begins to pay increasing attention to the demand side participation. There is an increasing number of renewable generation and a decreasing number of thermal generation on the network. The renewable generations increase the requirement of system balancing, which used to rely on the thermal generation. Therefore, National Grid expects DSR to achieve 30-50% of system balancing by 2050. National Grid has published Expression of Interest for a new Demand Side Response service, and an Enhanced Frequency Response service [57]. Currently, the DSR mechanism include Firm Frequency Response (FFR), Frequency Control Demand Management, Short Term Operating Reserve (STOR), STOR Runway, Demand side Balancing Reserve and the Capacity Market [21]. The full list is shown in table 2-1 [58].

Table 2-1 DSR integration strategies of National Grid

Capacity	Frequency	Reserve
<ul style="list-style-type: none"> • Transitional Arrangement • T-4 Auction • T-1 Auction 	<ul style="list-style-type: none"> • Fast Frequency Response (FFR) • FFR Bridging • Frequency Control Demand Management • Enhanced Frequency Response • 	<ul style="list-style-type: none"> • Short Term Operating Reserve (STOR) • STOR Runway • Demand Side Balancing Reserve • Fast Reserve

Majority of the investigations conducted by Distribution Network Operators (DNOs) are the innovation trials -- the Low Carbon Network Fund projects [12], such as Customer-led Network Revolution [32] and Sola Bristol [59]. This PhD research is

based on the latter DNO project, Sola Bristol, in which the aim is to find an innovative solution to enable high density photovoltaic solar generation to connect to LV network more efficiently through using energy storage, DC networks, and variable tariffs. The results show that given 85% network utilization, 50% domestic DSR penetration could bring network investment deferral up to £11000 per LV network. And customer could receive average £7.5/month across the year on electricity bill saving.

One of the typical domestic DSR schemes in the UK is the Economy 7 and 10 tariff for domestic customers, which provides off-peak price for seven or ten hours during the night. 20% of the UK customers have chosen this kind of TOU Tariff [16]. The typical load profile [46] of the customers adopting Economy 7 and 10 is shown in figure 2-4. This type of customer uses electricity to heat the electric storage heaters or hot water tanks and therefore have much larger demand. However, with the development of heat pump and electric vehicle, increasing number of customers will need larger demand and the TOU tariff will be one of the effective DSR schemes to relief the pressure on the network.

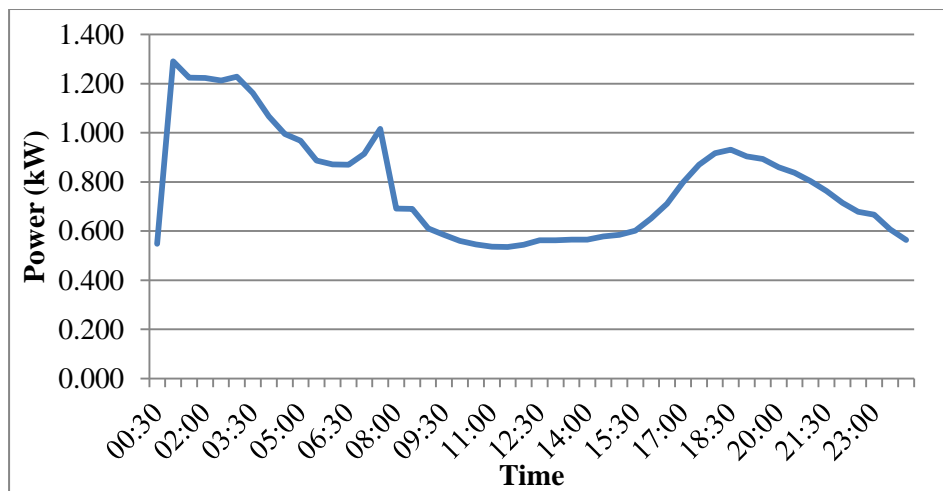


Figure 2-4 Typical load profile of Economy 7 customer

In summary, currently in the UK, distributed generation , I&C back up generation and I&C DSR have the access to the electricity market and have been investigated and implemented in wide range of the institutions. However, the domestic DSR and DNO smart grid technologies are currently under trial and have limited opportunities to contribute to electricity industry [60-62].

2.4.2 USA

In the USA, the DSR was initialized in the 1970s, with the spread of central air conditioning [63]. In late 1980s and 1990s, Direct load control and Interruptible/curtailable DSR schemes were popular and were adopted in some regulated utilities, such as Southern California Edison, but customers were rarely to be called to reduce the load and have not been exposed to the wholesale price signals or whole system. Since late 1990s, DSR scheme number reduced since the wholesale energy markets were built and the newly established regional grid operators relied on generation assets. In 2000, Direct load control and Interruptible/Curtailable DSR schemes were widely used since the wholesale market price roared and customers began to leave the schemes. At the same time, DSR providers were empowered to participate the market to reduce volatility and market price. DSR began to be supported by U.S. Federal since 2005 in the “Energy Policy Act of 2005” [64]. The official policy encouraged enabling technology and devices of DSR to be deployed.

However, the deployment of DSR is largely focus on large demand customers. The DSR is mostly used for wholesale, capacity and ancillary markets since the regulation acceptance and the amount and variety of load available for reduction from a single facility. The independent system operators (ISO), such as PJM and New England, have successfully incorporated significant amounts of DSR. As of 2010, PJM has achieved 10.5% of its peak load from DSR and New England has achieved 7.8% [22]. Few DSR schemes from small and medium customers have been approached. The regulation acceptance and small accommodations from system operators and regulatory agencies are required for the development of DSR among these customers.

2.4.3 Germany

In Germany, DSR schemes are currently being implemented in energy market [24]. Some major German energy-intensive industrial corporations offer flexible loads throughout their production processes on the national balancing market. Moreover, 1.2 GW of loads were prequalified on the demand response program “Abschaltbare Lasten”. Though, under today’s market conditions, loads are shifted only for the purpose of reducing network charges.

In the meantime, DSR is pushed toward further deployment in the Germany. On the aspect of regulatory environment, the current regulatory framework for DSR in Germany provides limited revenue possibilities for DSR owners and operators. As a consequence of this, the German Federal Ministry for Economic Affairs and Energy has announced a series of measures that will facilitate the access of DSR to wholesale and balancing markets in an electricity market white paper in 2015 [65]. On the national level, the German government is considering the introduction of a capacity mechanism. The Federal Ministry for Economic Affairs and Energy commissioned several studies, but there are no developed proposals for the mechanism yet and the government has not yet taken any formal decision on the introduction of a capacity market.

Similarly, in Germany, large consumers have more access to DSR than small consumers. There is more scope for cost savings through DSR for large consumers. More specifically, large consumers from energy intensive industries in Germany can already make use of the on and off-peak or even real-time tariffs. Some large consumers engage in load management to limit their peak demand or are shifting load to night time and weekends to reduce their energy bills. For small and medium consumers, there are currently limited opportunities for DSR. Off-peak supply tariffs are available from regional suppliers, which historically were aimed at the use of electric storage heaters. With storage heaters becoming less common, the corresponding night-time electricity supply tariffs now only play a limited role in the retail market, although some customers take advantage to switch appliance usage to the night.

2.4.4 Denmark

DSR is a key component of the Danish government's smart grid strategy [62]. The main motivation for increased demand side flexibility is better use of wind and other renewables by shifting demand to periods with high generation from wind power. Consequently the smart grid strategy includes the plans to introduce time-of-use tariffs and hourly settlement procedures, the details of which are still under development. Suitable smart meters are currently installed at 50% of all sites, which account for 75% of electricity consumption. Universal rollout of smart meters is planned by 2020.

Space and water heating plays a prominent role in demand side flexibility in Denmark. District heating with combined heat and power plants is already well

established in Denmark and provides approximately 50% of space and water heating. District heating could substitute surplus electricity for other fuels (such as biomass or gas) and thus use electricity when it is available in abundance. Energy in the form of heat can also be stored more easily so that district heating can be used for load shifting. Furthermore combined heat and power plants can provide flexible electricity generation capacity when run for their heat output. Danish energy company Dong Energy also invested in a programme for charging of electric vehicles which could provide additional energy storage and allow load shifting [66].

DSR from electric boilers for district heating already participates in the Danish balancing reserve markets, in particular for tertiary reserves. There are currently 35 sites with a total capacity of 275 MW participating in these markets. The total amount of tertiary reserves purchased by the system operator is approximately 1000MW. According to Smart Energy Demand Coalition (SEDC), an industry organization, participation of other demand side resources in the reserve markets is relatively small in comparison. SEDC highlights that participation in the primary reserve markets requires symmetrical bids for increases and reductions, which is a major barrier for demand side participation. Other barriers for participation named by SEDC include high minimum capacity, short dispatch notice and frequent activations.

Chapter 3. New Problem

Formulation of Home EMS for Maximum DSR Benefit

Significant LCTs, especially small-scale embedded generators and energy storage, will be accommodated at customer properties in the future. Department of Business, Energy & Industrial Strategy has published that the PV capacity nearly reaches 12GW by 2017. It is expected that the small-scale battery storage in domestic and commercial customers' place would rise from 400MWh now to 760GWh in 2040 [29]. These technologies are not only changing the original network operation philosophy, but also offering more demand flexibility to end users. As a consequence, the LCTs could play important role in DSR.

Therefore, this chapter proposes an innovative problem formulation to optimally integrate renewable generation and energy storage into DSR and maximize the benefit for the customers with the trigger of smart pricing.

3.1 Introduction

Given increased penetration of LCTs in customers', the energy management system (EMS) is gaining importance to optimize the operation and cooperation of LCTs for DSR. EMS is the inevitable tool to achieve: 1) full utilization of renewable energy by coordinating local energy generation and consumption; 2) reduced uncertainty brought by renewable generation [23, 67]; and 3) maximal the financial benefits to end customers.

The growing popularity of EMS in smart homes has led to researches focus on designing home energy management for energy storage operation. A home EMS (HEMS) control strategy has been developed in [68] that coordinates energy storage and home appliances aimed at lowering total electricity cost. The design introduces a user-expected price as an indicator of the differential pricing structure for different customers. In [69] a household energy storage control strategy is presented that manages domestic electric energy consumption. The battery dispatch strategy of this design considers both energy price and network pressure to facilitate DSR. Research in [70] presents a smart home load commitment strategy, i.e., the optimal operating periods of household appliances, including a consideration of the operating modes of electric vehicles (EVs) and storage. The work in [71] presents a HEMS with EV charging that factors in peak power limiting to facilitate DSR.

There are other studies that take renewable generation into consideration. In [72], the authors design an optimal scheduling of distributed energy resource (DER) to maximize the benefit for customers. A co-evolutionary version of particle swarm optimization (PSO) is used in this study to determine the operation of several DERs, including distributed generation (DG), energy storage, and controllable load. The work in [73] presents optimal power management for PV holders factoring in battery aging. The proposed management in this work is based on dynamic programming and is applied to real conditions. The work in [74] investigates real time scheduling of controllable loads, battery, and PV based on rule based fuzzy logic controllers. The stochastic characteristic of electricity price, temperature PV generation is considered. The study in [75] divides the stochastic household load (including renewable generation) into two types: the inelastic and elastic. The two load types are built with different models and optimized together. Load forecasting as well as an appliance-scheduling scheme is the focus in [76] to improve demand response. The adaptive neuro-fuzzy algorithm is developed to learn and predict electricity demand and a branch and bound based appliance schedule scheme is used. The operation of the scheduled appliance shifts when solar power is available and is incentivized with time of use (TOU) tariff, which is then updated by the forecasted load. The research in [77] proposes a HEMS strategy based control of a smart home to achieve DSR, including PV and availability of EV and storage. The energy management is achieved by simulation based optimization, i.e. the optimization process is based on repetitive simulations of the model with different parameter. Authors in [78] propose HEMS for evaluating the collaboration of dynamic pricing, renewable generation, EV, and energy storage, in which the EV and storage facilitate the DSR by trading energy between home and grid. Finally, in [39] optimal household electrical and thermal generation scheduling is developed in a hybrid thermal/electric grid home, which includes a fuel cell with combined heat and power (CHP) and a battery as the electricity storage system.

The choice of the method to solve the optimal energy management is determined by the nature of the problem. The real-time updated EMS requires model capable of dealing with uncertainty. The final optimal EMSs are always achieved by rule-based approaches, including fuzzy theory [74], or optimization methods for dynamical systems [75]. The problem that to find the optimal scheduling in a finite horizon with the demand/generation as input data, could be further divided into two categories. The

first is the optimal scheduling of the individual controllable appliances. The challenge of the problem is to optimize the on and off/low power mode of the controllable appliances. The final optimal scheduling is always achieved by rule-based approaches [68, 69, 71, 76] or heuristic-based optimization approaches [72]. The second category is to optimize the power flow within the household. The most commonly used techniques are optimization programming, such as linear programming/mixed integer linear programming [70, 78], dynamic programming [73], quadratic programming and heuristic based optimization [39]. The linear programming/mixed integer linear programming needs low computing resources but has no applicability to reactive optimization (real-time modification problem). The dynamic programming requires high memory when time step is high but could resolve all types of problems, including linear and nonlinear, convex and concave etc.. The quadratic programming solving the non-linear programming needs the objective function to be convex and could be hard to find optimal solutions if the variables is high quantity. The heuristic optimization, like the dynamic programming, could solve all types of the problems. But its optimal results depend on the initial point and parameters.

The main purpose of this work is to find the optimal power flow that minimizes the total energy cost over scheduling period (one day). In this chapter, a new formulation-piecewise function formulation is proposed for optimizing the battery charging and discharging behavior with the integration of renewable generation. The advantage of the formulation is it simplifies the optimization process while keeps the accuracy and effectiveness of the optimization model. The formulation transfers all the information of possible power flow, price, battery capacity and conversion efficiency into the relationship between battery energy and final energy cost. The objective is to propose a simple DSR algorithm with less computational burden and will be easier to implement in practice. The relationship is represented by piecewise functions and easily solved by mixed integer linear programming.

The rest of the chapter is organized as follows: Section 3.2 demonstrates the smart EMS system in customers' premise; Section 3.3 introduces the optimization model to achieve maximum DSR benefit given TOU tariff; Section 3.4 proposes the piecewise function formulation for optimization model that simplifies the solving process; Section 3.5 presents a case study to illustrate the effectiveness of the proposed method; Section

3.6 draws the conclusion.

3.2 Overview of EMS system

The simple structure of a smart home is shown in figure 3-1. A smart home will consist of the following: renewable generation, use of battery, and loads [59]. With the help of a battery, PV output can be fully used to fulfil high demands during evening peak periods; in this way, customers can take advantage of tariffs to save on their electricity bills and also participate in DSR to reduce network pressure.

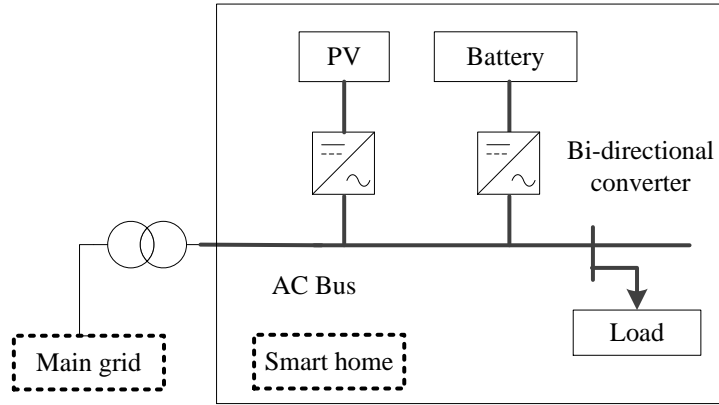


Figure 3-1 Overview structure of smart home

To achieve optimal energy usage in the smart home, a home energy management system (EMS) is built as shown in figure 3-2. The EMS takes the input data of forecasted customer load data, PV output, and tariffs. Then based on the objectives and constraints, it generates a strategy for battery charging and discharging. The control strategies are sent to a charge controller and a bi-directional converter in order to achieve the needed state of charge (SOC) of the battery.

In the EMS, distributed generation and load information are derived from historical data. The methods for forecasting PV generation are widely introduced in [79-81]. Load forecasting methods are investigated in appliance scheduling studies, such as in [76]. For simplicity, it is assumed that forecasted PV output and load data are available at least one day ahead in the optimization model in this study. Also, it is assumed that there is minor error in the forecasting and it will not influence the DSR optimization algorithm. The EMS will generate the battery operation schemes in advance before the

beginning of a day.

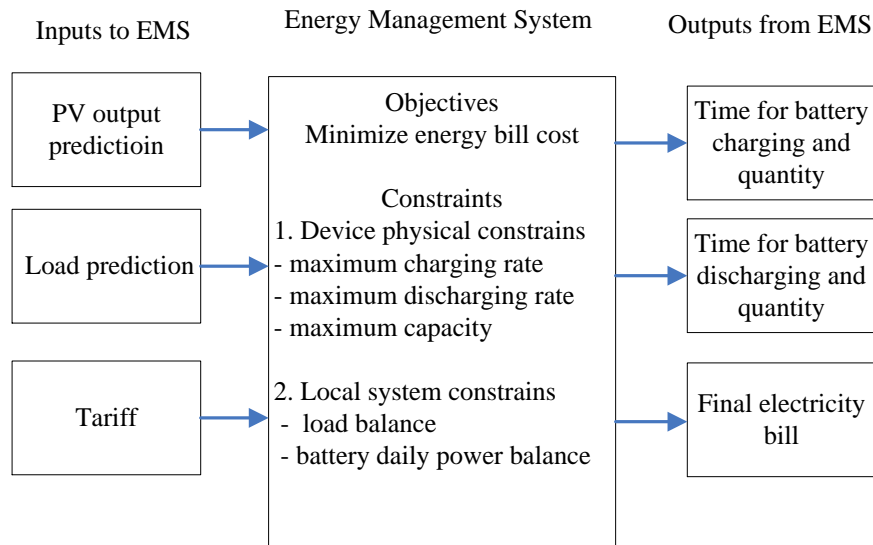


Figure 3-2 Energy management system

3.3 Optimal HEMS control strategy

In this section, the mathematical formulation of household optimal power management is presented. The objective is to minimize the total energy cost over scheduling period (one day). It is assumed that the amount of demand and PV output are available from the forecast. Thus, the battery and converter operation is designed with the response to price incentive.

A. Objective

The objective of battery operation is to minimize the cost of purchasing electricity from the main grid.

$$\text{Min} \sum_{t=1}^{96} C(t)P(t)T \quad (3-1)$$

Where, $C(t)$ is the TOU rate at time t , $P(t)$ is electric power required from the main grid at time t , T is the length of time settlement, which is a constant. In this model $T=0.25$ h, and the total time slot is 96.

In this study, it is assumed that selling electricity price (export rate) is zero because

there is no local energy market. Therefore, $C(t) = 0$, when $P(t) < 0$.

The required power is determined by loads, battery charging/discharging power and PV generation, as shown in equation 3-2. Since battery is charged or discharge with DC power, there will be an AC-DC power conversion during charging and discharging period. The conversion efficiencies, including AC/DC converter efficiency and battery efficiency, are considered in equation 3-3.

$$P(t) = P_{load}(t) + P_S(t) - P_{PV}(t) \quad (3-2)$$

$$P_S(t) = \begin{cases} \eta_C P_{S-in}(t) & \text{if } P_{S-in}(t) > 0 \\ 0 & \text{if } P_{S-in}(t) = 0 \\ \eta_D P_{S-in}(t) & \text{if } P_{S-in}(t) < 0 \end{cases} \quad (3-3)$$

Where, $P_{load}(t)$ is the loads of the house, $P_S(t)$ is the power of battery taken from or input to home local network, $P_{PV}(t)$ is the PV power, $P_{S-in}(t)$ is the power charged into or discharged from battery. When the battery charges, $P_{S-in}(t) > 0$; when discharges, $P_{S-in}(t) < 0$; when battery is idle, $P_{S-in}(t) = 0$. η_C is the efficiency when battery is charging, η_D is the efficiency when battery is discharging. Since there is energy loss during the AC/DC conversion, $P_S(t) > P_{S-in}(t)$, when $P_{S-in}(t) > 0$; and $|P_S(t)| < |P_{S-in}(t)|$, when $P_{S-in}(t) < 0$. Therefore, $\eta_C > 1$ and $\eta_D < 1$ with $\eta_C = 1/\eta_D$.

B. Constraints

In the proposed model, the constraints of devices and power balance should be satisfied, which are:

Battery charging and discharging rates should be within certain ranges, which are constrained by its physical properties.

$$P_D^{max} \leq P_{S-in}(t) \leq P_C^{max} \quad (3-4)$$

Where P_D^{max} and P_C^{max} are maximum discharge and charge rate of the battery.

The amount of energy stored in the battery is limited:

$$E_{min} \leq E(t) \leq E_{max}, \quad t = 1, 2, \dots, 95 \quad (3-5)$$

Where $E(t)$ is the stored energy in the battery at time t . E_{min} and E_{max} are battery minimum and maximum capacity. In this model, the initial energy storage in the battery is set at its minimal limit, i.e. $E(0) = E(96) = E_{min}$. It should be noticed that the minimal limit E_{min} also could be set at the start of off-peak price in the evening. Specifically, the stored energy in the battery is accumulated through its charging/discharging process.

$$\begin{cases} E(t) = E(t-1) + \Delta E(t) & t = 1, 2, \dots, 96 \\ \Delta E(t) = P_{S-in}(t)T \end{cases} \quad (3-6)$$

The battery is operated on a daily basis. To ensure it has enough headroom for the next day, the sum of charging and discharging power of one day is assumed to be zero:

$$\sum_{t=1}^{96} P_{S-in}(t) = 0 \quad (3-7)$$

3.4 Problem formulation

This chapter proposes a new problem formulation called piecewise function formulation. In the proposed model, the relationship of final energy cost and battery power is built by piecewise functions for each time slot. The piecewise functions are then converted to mixed integer model for optimizing. Finally, the mixed integer model is resolved by MILP.

3.4.1 Building of piecewise function

In the DSR strategy optimization model, piecewise functions are built to final energy cost and battery power relationship.

A. The piecewise functions of final demand and battery power

Firstly, the relationship between customer final demand and battery power can be directly represented as linear functions. Based on equations 3-1, 3-2 and 3-3, at each

time slot, the power drawn from the main grid is the sum of battery power and other demand. The equations can be simplified represented as equation 3-8.

$$P(t) = A \times P_{S-in}(t) + D \quad (3-8)$$

Where A represents the conversion efficiencies, D represents the sum of customer load and PV output.

Then, based on equation 3-8, several scenarios could be enumerated between final demand and battery power as shown in table 3-1.

Table 3-1 Piecewise function scenarios

Scenarios		Explanations
$A > 1$	$D > 0$	Battery charges; load is larger than the PV output
$A > 1$	$D < 0$	Battery charges; load is smaller than the PV output
$A < 1$	$D > 0$	Battery discharges; load is larger than the PV output
$A < 1$	$D < 0$	Battery discharges; load is smaller than the PV output

The linear relationship between final demand and battery power can be represented by a piecewise function. The examples of the built piecewise function are shown in figure 3-3 and figure 3-4. Y-axis, $P(t)$, and x-axis, $P_{S-in}(t)$, are the electrical power purchased from the main grid and battery power respectively.

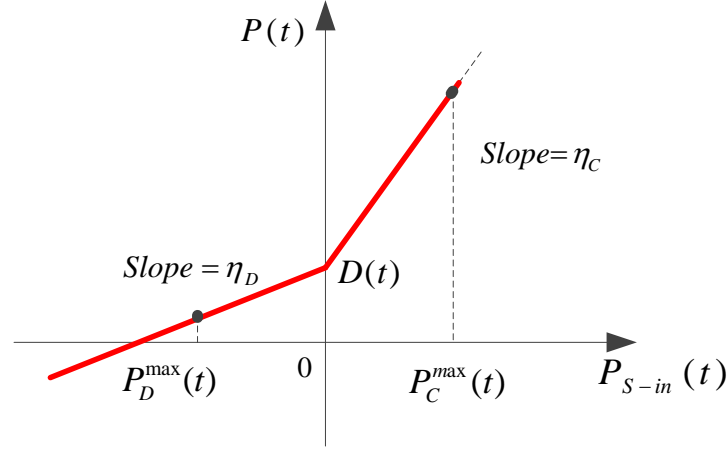


Figure 3-3 Piecewise function when demand is larger than PV output

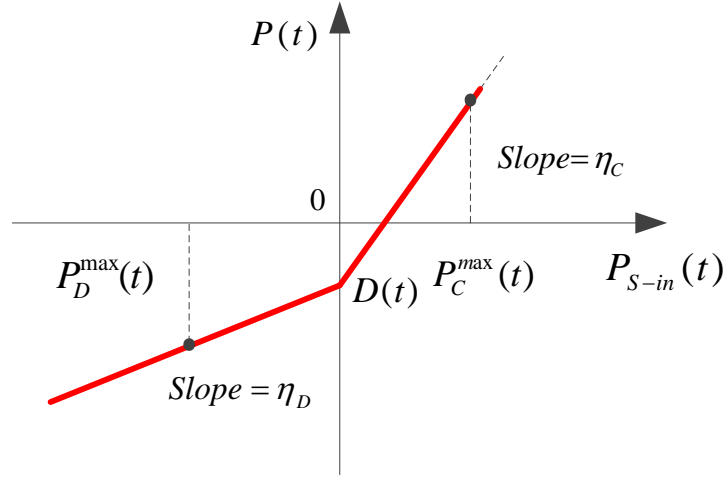


Figure 3-4 Piecewise function when demand is smaller than PV output

The piecewise function of each time slot is built after defining slopes, breakpoints and the power value range. The slopes of the piecewise functions are determined by the conversion efficiencies, as coefficient A in equation 3-8. When battery is charged, $P_{S-in}(t) > 0$, the slope of is greater than 1, since part of charging power becomes conversion losses, i.e. $\frac{P_S(t)}{P_{S-in}(t)+Loss} = 1$. When battery is discharged, $P_{S-in}(t) < 0$, the slope of is less than 1, since part of discharging power becomes conversion losses, i.e. $\frac{P_S(t)+Loss}{P_{S-in}(t)} = 1$. The values of breakpoints of piecewise function are determined by non-battery demand, represented as D in equation 3-8. There is a power range in the piecewise function, which is determined by the minimum and maximum power rate of

the battery.

B. The piecewise functions of final energy cost and battery power

The price information can be added to demand piecewise functions as coefficients of demand, $P(t)$. The simplified representation of final energy cost and battery power can be derived as equation 3-9.

$$C(t) \times P(t) = C(t) \times A \times P_{S-in}(t) + C(t) \times D \quad (3-9)$$

The piecewise functions of $C(t) \times P(t)$ would become several shapes after adding the price information. Since it is assumed that selling price is zero, $C(t) \times P(t) = 0$, when $P(t) < 0$, the piecewise function of final energy cost and battery power is largely different from that of final demand and battery power. Depending on the relationship between price, non-battery demand, value range, and charge and discharge efficiencies, there will be four main scenarios as shown in figure 3-5 to figure 3-8. Therefore, for each time slot, the piecewise function of $C(t)P(t)$ might range from three segments to one segment.

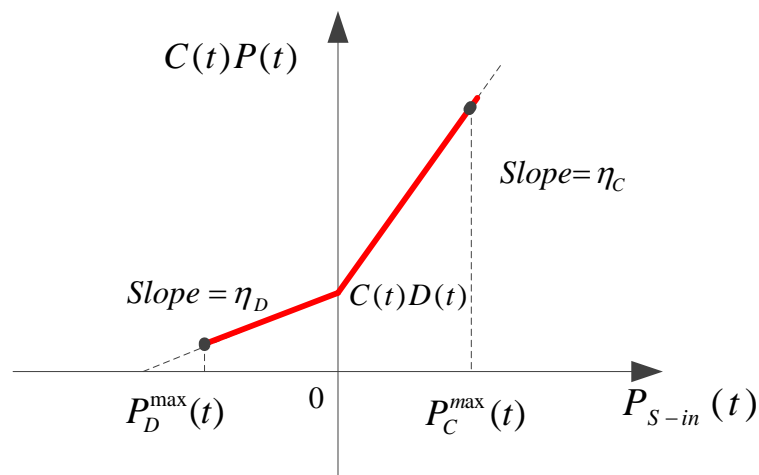


Figure 3-5 Piecewise function of scenario 1

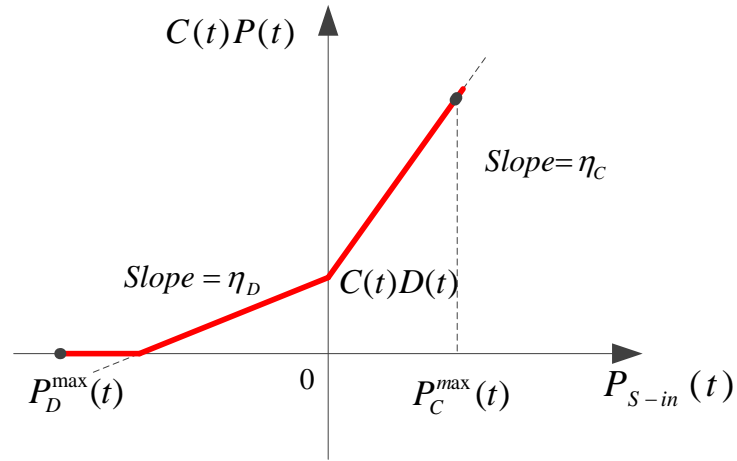


Figure 3-6 Piecewise function of scenario 2

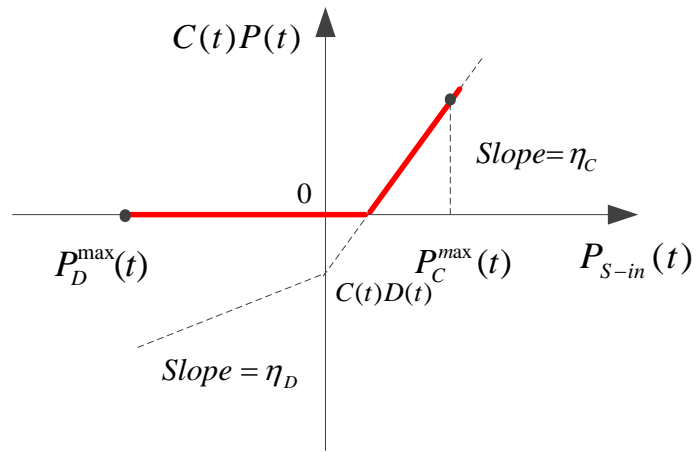


Figure 3-7 Piecewise function of scenario 3

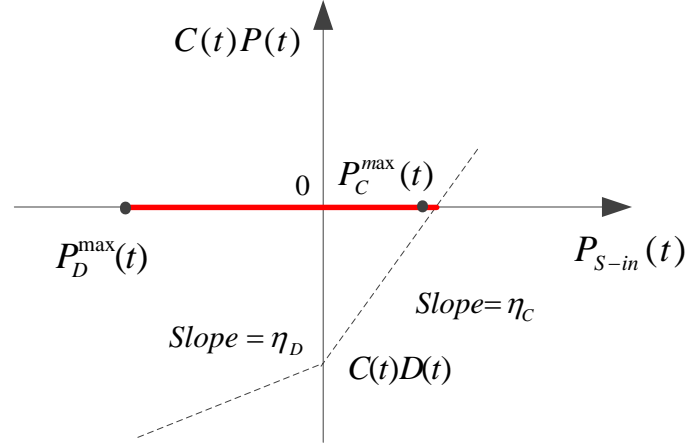


Figure 3-8 Piecewise function of scenario 4

3.4.2 Conversion of piecewise function into mixed integer model

The piecewise functions could be directly converted into a mixed integer model by introducing virtual variables: $w_n(t)$ and $z_n(t)$. If there are more than one segment in the piecewise function at this time slot, both battery power, $P_{S-in}(t)$ and the cost of electricity, $C(t)P(t)$, are replaced with a set of virtual variables: $[w_n(t), z_n(t)]$, in which, $z_n(t) = 0$ or 1 . If there is only one segment at this time slot, as shown in the figure 3-8, variables do not need to change since final energy cost is zero.

The binary integer variables $z_n(t)$ represent the segments in the piecewise function. At each time slot, the number of binary variable $z_n(t)$ equals to the number of segments of piecewise function. $z_n(t)$ is a 0-1 integer: $z_n(t) = 0$ means the optimal battery power is not in this segment; $z_n(t) = 1$ means the optimal battery power is in this segment. The sum of $z_n(t)$ needs to be one since only one segment will be in the final solution. The mathematical representation is:

$$\begin{cases} \sum_{n=1}^{m-1} z_n(t) = 1 & (m = 2, 3, 4) \\ z_n(t) = 0 \text{ or } 1 \end{cases} \quad (3-10)$$

The variables $w_n(t)$ determine the specific value of battery power in the appointed

segment, which are the coefficients of the breakpoints. The number of variable $w_n(t)$ equals to the final number of breakpoints of piecewise function. The constraints and relationships are as follows.

$$\begin{cases} \sum_{n=1}^m w_n(t) = 1 & (m = 2,3,4) \\ w_n(t) \geq 0 \end{cases} \quad (3-11)$$

$$\begin{cases} w_n(t) \leq z_n(t) & \text{if } n = 1 \\ w_n(t) \leq z_{n-1}(t) & \text{if } n = m \\ w_n(t) \leq z_{n-1}(t) + z_n(t) & \text{else} \end{cases} \quad (3-12)$$

Specifically, if there are three segments, breakpoint number is 4 and $m=4$; if there are two segments, breakpoint number is 3 and $m=3$.

In detail, the battery power is represented by virtual variables, $w_n(t)$ and values of breakpoints on x-axis, $B_n(t)$. Where, $B(t)$, is the crossing point of piecewise function and x-axis.

$$P_{S-in}(t) = \sum_{n=1}^m B_n(t)w_n(t) \quad (m = 2,3,4,5,6) \quad (3-13)$$

$$B_n(t) \in [P_D^{max}(t), B(t), 0, P_C^{max}(t)]$$

The cost of electricity, $C(t)P(t)$ is also represented by virtual variables, $w_n(t)$ and values of breakpoints on y-axis, $A_n(t)$.

$$C(t)P(t) = \sum_{n=1}^m A_n(t)w_n(t) \quad (m = 2,3,4) \quad (3-14)$$

$$\frac{A_n(t)}{C(t)} \in [0, D(t), P(P_c^{max})]$$

The final optimization model can be represented as:

A. Objective

$$\text{Min} \sum_{t=1}^{96} \sum_{n=1}^m A_n(t) w_n(t) T \quad (m = 2, 3, 4) \quad (3-15)$$

B. Constraints

$$\begin{cases} \sum_{t=1}^{48} \sum_{n=1}^m w_n(t) = 1 \quad (m = 2, 3, 4) \\ w_n(t) \geq 0 \end{cases} \quad (3-16)$$

$$\begin{cases} w_n(t) \leq z_n(t) \quad \text{if } n = 1 \\ w_n(t) \leq z_{n-1}(t) \quad \text{if } n = m \\ w_n(t) \leq z_{n-1}(t) + z_n(t) \quad \text{else} \end{cases} \quad (3-17)$$

$$\begin{cases} \sum_{t=1}^{48} \sum_{n=1}^{m-1} z_n(t) = 1 \quad (m = 2, 3, 4) \\ z_n(t) = 0 \text{ or } 1 \end{cases} \quad (3-18)$$

The amount of energy stored in the battery should meet

$$E_{min} \leq E(0) + \sum_{t=1}^{95} \sum_{n=1}^m B_n(t) w_n(t) * T \leq E_{max} \quad (3-19)$$

$$(m = 2,3,4)$$

The sum of charging and discharging power of one day is assumed to be zero:

$$\sum_{t=1}^{96} \sum_{n=1}^m B_n(t)w_n(t) = 0 \quad (m = 2,3,4) \quad (3-20)$$

As a result, the piecewise function is converted to 0-1 integer linear model with $A_n(t), B_n(t), w_n(t), z_n(t)$. The battery operation scheme can be directly resolved by MILP.

3.5 Demonstration

In this section, the performance of the proposed HEMS is demonstrated on smart homes with different load profiles, differing storage capacities and current limits, and converter efficiencies and PV output. The battery control strategy and benefits of bill saving of each case is shown and discussed.

Battery parameters used in HEMS framework are shown in table 3-2. The lithium-ion battery is chosen as the example energy storage because of its high performance, safety, and long lifetime when compared with other types of batteries.

Table 3-2 Battery parameters

Battery Parameters	Value
Capacity	4.8 kWh (200Ah)
Voltage	24V
Charging current limit	20A ($\leq 10\%$ of rated AmpHours)
Discharging current limit	20A ($\leq 10\%$ of rated AmpHours)
Max/Min SOC	0.9/0.3
Charge/discharge efficiency	90%

In this study, TOU tariffs derived from wholesale energy price are used [23], as shown in table 3-3. The wholesale energy cost in Great Britain (GB) mainly determines

the electricity bills of the customers because it accounts for over half of customers' electricity bills [24]. It is expected that this situation would continue in the future [25]. Additionally, the used TOU tariff could reflect the pressure on network, i.e. the peak price could match up with the peak demand during evening. Thus, the TOU tariff triggers demand reduction during peak demand and bring benefit to the network.

Table 3-3 TOU tariffs

Tariff Type	Time	Price (£/MWh)
Tariff 1 (low price)	00:00–06:59	146.08
	14:00–16:29	
	21:00–23:59	
Tariff 2 (shoulder price)	07:00–13:59	181.45
	19:00–20:59	
Tariff 3 (peak price)	16:30–18:59	241.27

The PV capacity is 1.5 kWp, and the PV output is shown in figure 3-9. It should be noticed that the peak power of PV may be greater than the battery maximum charging power.

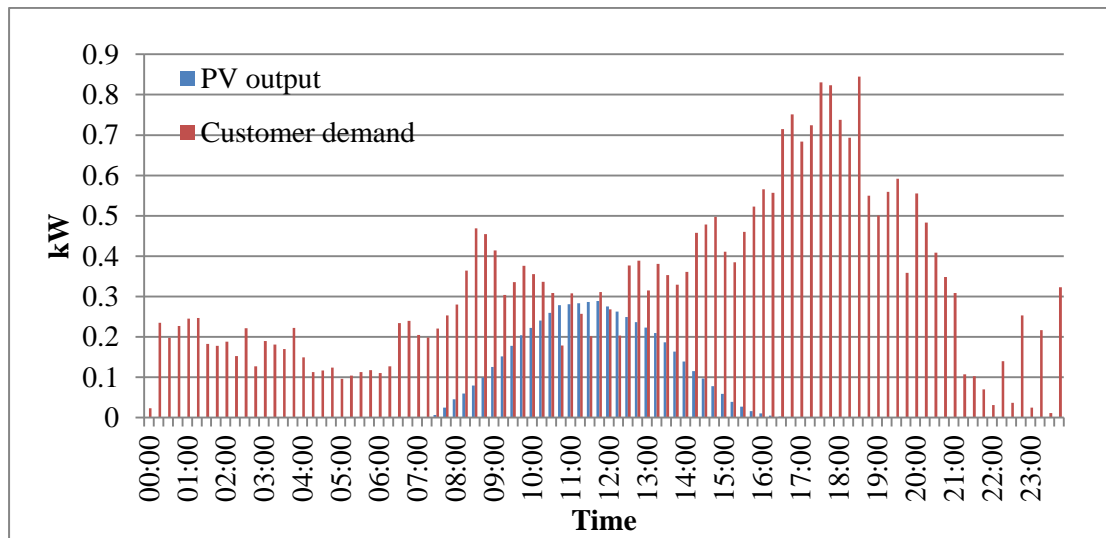


Figure 3-9 Customer demand and PV output

3.5.1 DSR performance of customers

The battery control strategy and corresponding demand change on a weekday are shown in figure 3-10 and figure 3-11. As depicted in figure 3-10, battery charges during low price times in the early morning and afternoon to 79% and 74% of SOC, respectively. It discharges in the shoulder price to 56.5% of SOC with lower rate in the peak price to minimum 30% of SOC with higher rate. The battery capacity is not fully

utilized (it only charges to 79% SOC in the morning), because the PV output is enough to supply the daily demand without the help of battery. Consequently, the demand in low price periods increases significantly as the battery charges from the main grid. The demand in the daytime decreases to zero as surplus PV and battery output power supports demands. The evening demand peak is reduced by nearly half using the battery, with the incentive of peak price.

The daily bill savings for this type of customer is £0.31. Compared to the original electricity bill, EMS reduces the electricity bill by 21.96%. In 2016, the cost of PV and battery with installation is £5700 [82, 83], the annual rate of return is 2%. However, the cost of EV battery dropped 80% in 6 years and PV might reduce 59% by 2025 compared with 2015 [84, 85]. The rate of return could increase largely in the future time.

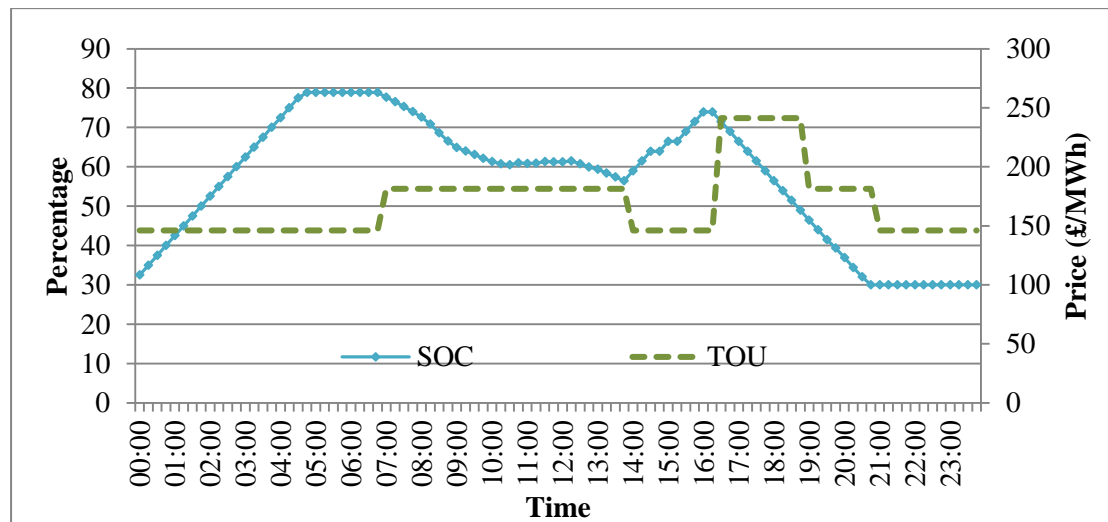


Figure 3-10 Battery SOC

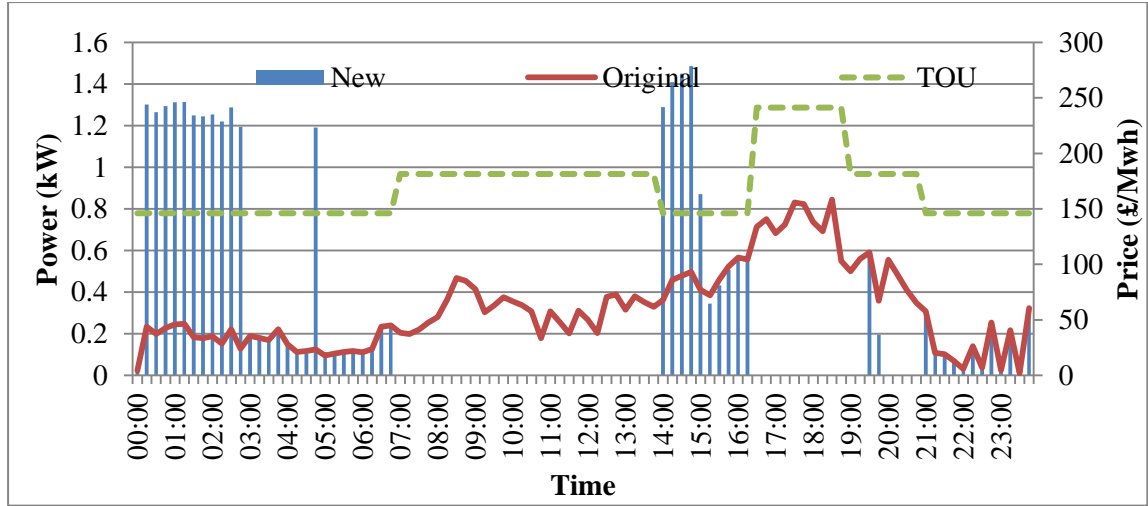


Figure 3-11 Demand change after DSR

3.5.2 Sensitivity analysis

A sensitivity analysis is performed to assess the impact on EMS performance in different types of houses, battery charge rate, and converter efficiencies. The resulting change in battery control strategies and bills savings are plotted and listed.

1. Impact of load profiles

Currently, in the U.K., there is a group of customers have electric heat demand overnight hours. However, with the electrification of heating and transport, the electricity demand of end customers will grow in the future. Additionally, the electric heat demand will become time unlimited. Both electric resistance heating and heat pumps will be widely deployed to achieve low carbon heat [86]. A recent investigation of domestic demand has shown heat pump consumption represented a significant additional electrical load when compared with a gas heating system in normal homes, accounting for 122% of total electricity consumption [87]. Additionally, demand for heat is often highest in the evening peak periods. Therefore, in the future, electric heating demand will not be seen as restricted to just overnight use. There will be increasingly large electric heating demand during the entire day.

The EMS performances of houses with heat load are assessed in this section. The electricity demand of houses with heat load is larger than normal houses. The loads are clustered into three types to demonstrate the impacts of load characteristics: overnight

heat load, daytime heat load, and evening heat load as shown in figure 3-12.

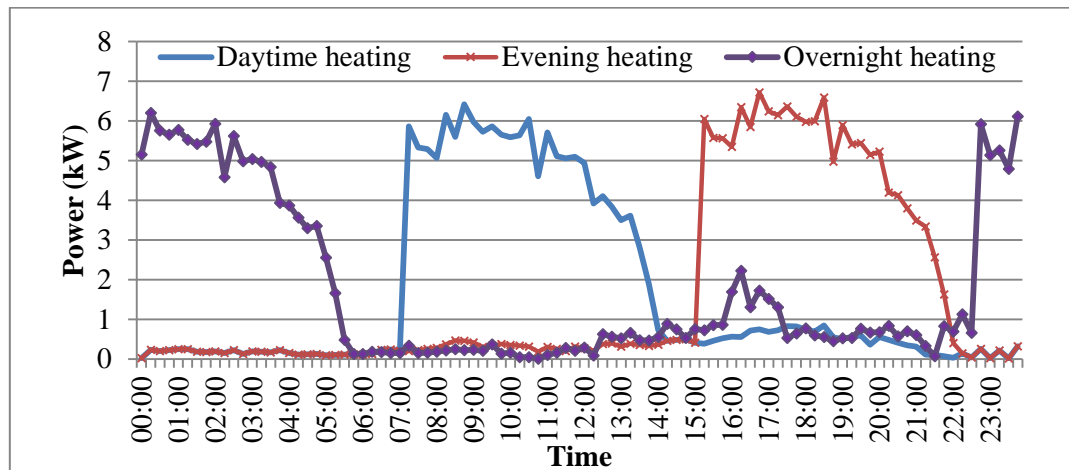


Figure 3-12 Load profiles of three types of electric heat customers

The battery control strategies of three types of demand and original normal demand are shown in figure 3-13. The overnight heating customer's battery discharges small amount of energy during shoulder price time. However, it is charged more by the PV output during the morning and noon in order to support demand with maximum rate during the evening peak time. The battery of the daytime heating customer discharges 49% of its available stored energy in the daytime to support large daytime heat demand. The battery behaviour of evening heating customer is similar to a normal customer in that it charges at a low price time and discharges with a maximum rate at high price and high demand time.

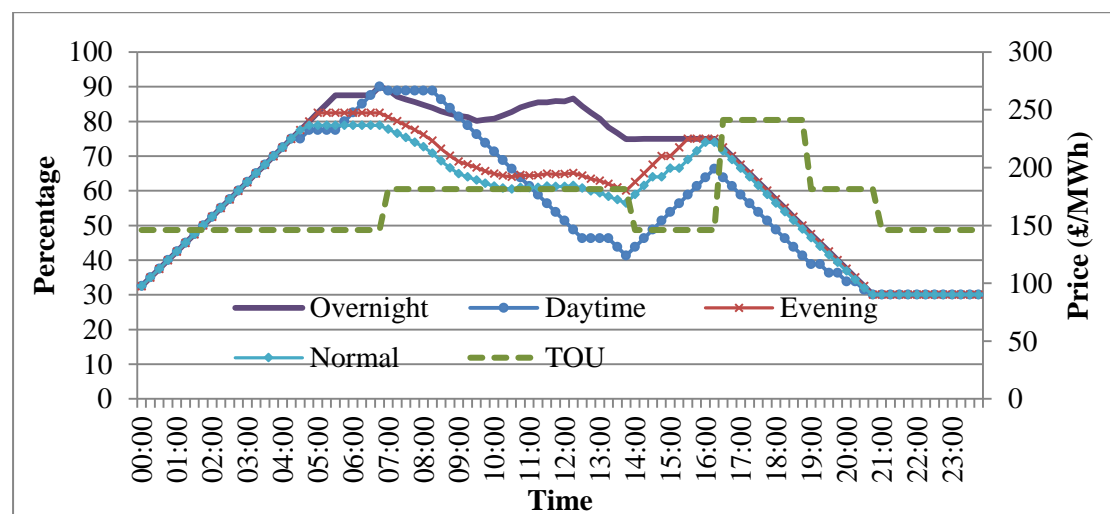


Figure 3-13 Battery SOC of four types of load profiles

The compared load profiles before and after EMS are shown in figures 3-14 to figure 3-16. The EMS effectively removes the demand from high price and shoulder price time to low price time. The battery puts much of its effort on supporting the large heating demand. However, as shown in figure 3-15 and figure 3-16, the amount of demand reduction and shifting is limited compared to the large electric heating load during the daytime or evening.

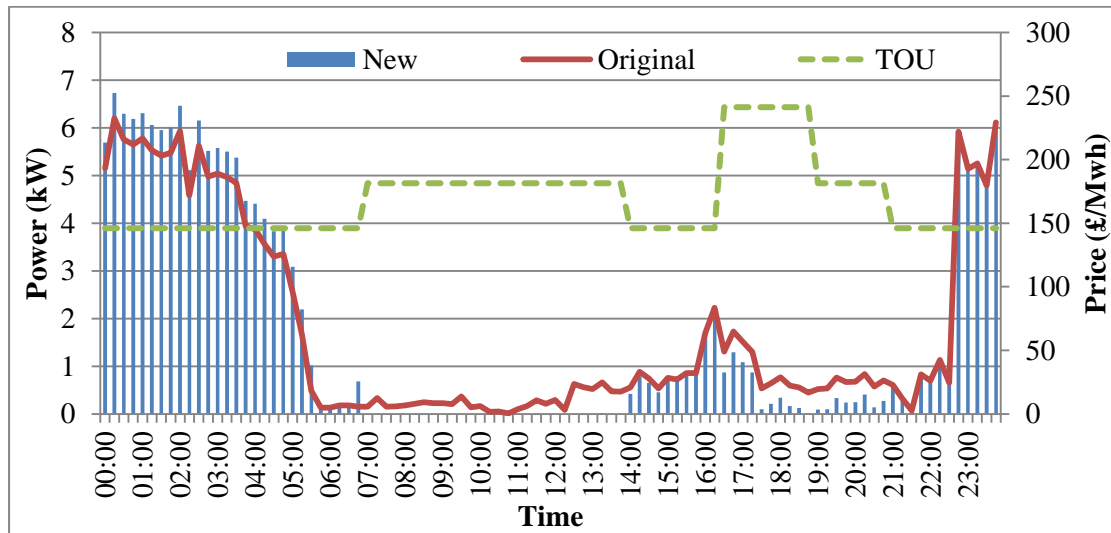


Figure 3-14 Demand change of overnight heating customer

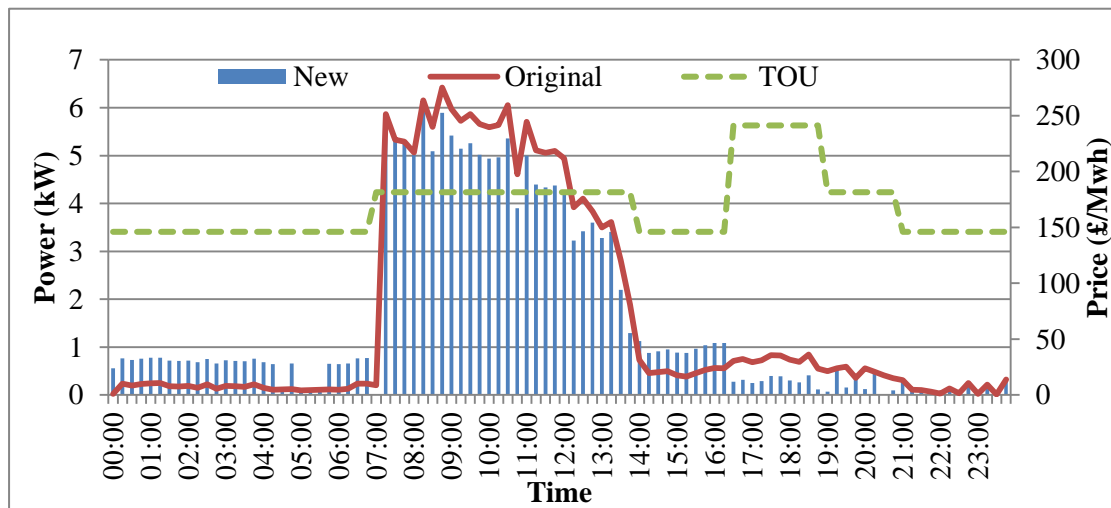


Figure 3-15 Demand change of daytime heating customer

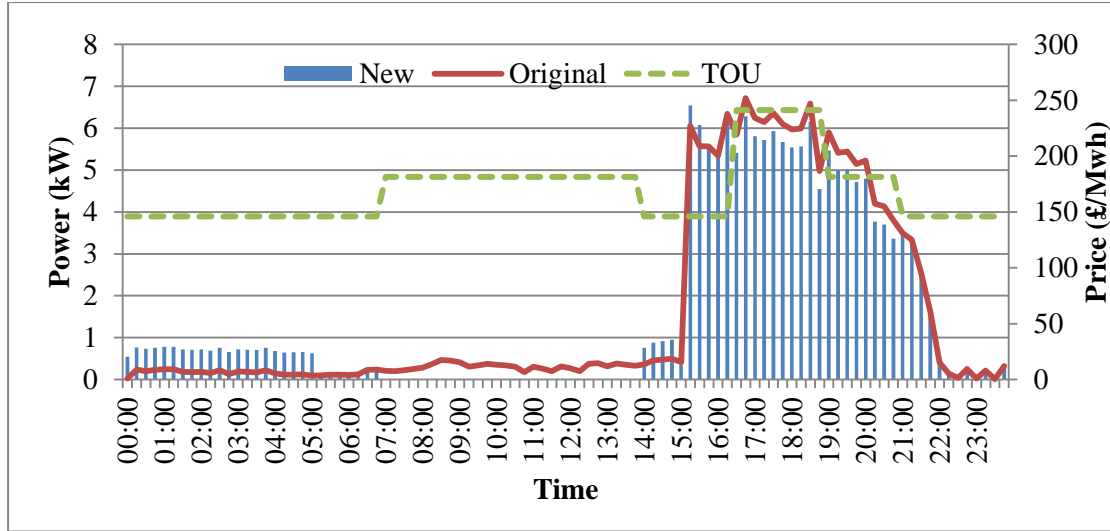


Figure 3-16 Demand change of evening heating customer

The daily bill savings for the scenarios are shown in table 3-4. The savings are all around £0.31 compared with the case without EMS. The saving of daytime heating customers is the largest. At the daytime heating customer's house, the PV output and demand peak is overlapped. Therefore, both PV and battery could fully contribute to demand reduction and bill saving. The saving of overnight heating customer is least. It is shown in previous figure that the battery operate less in overnight heating customer's home compared with others. Since the daytime demand is relatively low, the battery function of shifting demand in overnight heating customers' home is not as essential as that in other customers' home. The original electricity bill for overnight heating customer is lower than the two counterparts. Therefore, the saving percentage is the largest, at 4.65%. However, since the original electricity bill of customer with electric heating is large, the saving percentage of the electric heating customer is relatively smaller compare to the normal customer.

Table 3-4 Bill savings of different types of customers

Customer Type	Daily Bill Saving (£)	Saving Percentage (%)
Normal	0.31	21.96
Overnight heating	0.30	4.65
Daytime heating	0.32	4.39
Evening heating	0.31	4.08

In summary, it can be observed that 1) the battery control strategies can be greatly affected by load profiles; 2) larger benefit will be brought in daytime high demand customers using the battery and EMS given high price during the day; 3) the battery is

less important in overnight high demand customers.

2. Impact of battery charge rate

Battery charge rate determines the demand shift capacity of battery and thus influence the bill savings. The battery charging and discharging current limit directly reflect battery charge rate. It is seen that the battery charging/discharging limit increases to 30A and 40A.

The battery control strategies with different charge rates are shown in figure 3-17. Different with based case of 20A current limit, the battery with increased charge rates make full use of its capacity. Therefore, increased amount of demand is shifted from peak to off-peak time. During early morning and afternoon off-peak price time, the battery is charged to 90% of SOC. The strategies of 30A and 40A have minor differences. The SOC of 40A battery discharges fast during peak price time. As shown in table 3-5, by increasing the battery charge rate, the bill savings of houses increase, since increased amount of demand during peak time could be shifted to off-peak price time. However, the incremental saving is reduced: bill saving increases 2.22% in the cases from 20A to 30A while it increases 1.03% from 30A to 40A.

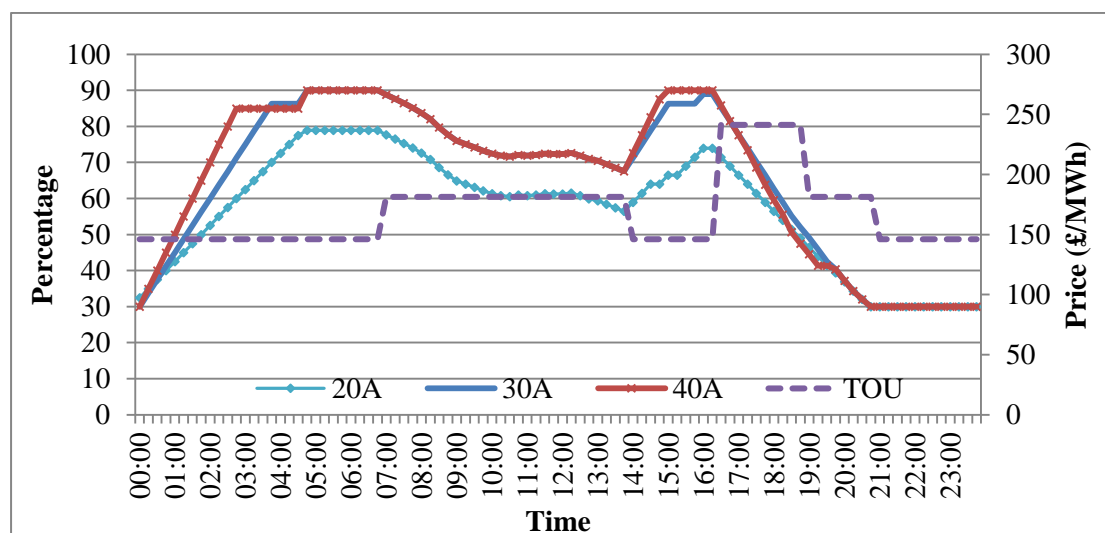


Figure 3-17 Battery SOC with different battery charge rates

Table 3-5 Bill savings with different battery charge rates

Battery charge rate	Daily Bill Saving (£)	Saving Percentage (%)
Base 20Ah	0.31	21.96
30Ah	0.34	24.18
40Ah	0.36	25.21

In summary, the increased battery charge rate could bring increased electricity bill savings. However, the incremental benefit will be reduced after reaching certain battery charge rate.

3. Conversion efficiency

Converter efficiency, including both battery and converter efficiency, determines the energy loss in the system, and thus is an important factor in electricity bills. The battery control strategy with converter efficiency of base case 90%, 87%, 85% and 92% are compared

As shown in figure 3-18, although the battery makes full use of its capacity when the conversion efficiency increased to 92%, the charge and discharge patterns between the two scenarios are the same. In the case of 90% efficiency, battery is charged more during afternoon off-peak price time, while, in the case of 92% efficiency, battery is charged more during morning off-peak price time.

The results show that the battery control strategies of 85% and 87% conversion efficiencies are the same. The battery does not shift the demand in shoulder price under these efficiency condition because the money losses (caused by energy losses) during the inefficient demand shifting are larger than the benefits brought by demand shifting. The battery only shifts demand during peak price times. With the battery current limit and peak price time limit, the shifted AC demand is limited. In this case, the shifted demand only account for a maximum of 55% of battery capacity. It can be predicted that if the efficiencies keep decreasing, the battery may not work since the money loss cannot be compensated for by the benefit brought by demand shifting between peak price and low price.

The daily bill savings is directly related to conversion efficiency. Therefore the saving increases with the conversion efficiency increase as shown in table 3-6.

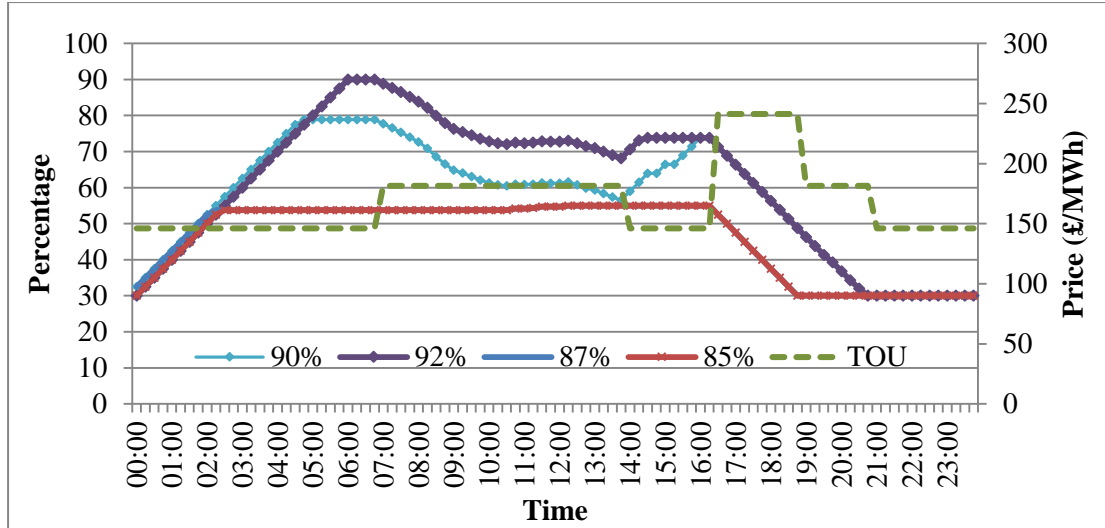


Figure 3-18 Battery SOC with different conversion efficiencies

Table 3-6 Bill savings with different conversion efficiencies

Conversion efficiency	Daily Bill Saving (£)	Saving Percentage (%)
Base 90%	0.31	21.96
92%	0.33	23.69
87%	0.29	20.72
85%	0.28	19.98

To conclude, under a given TOU price condition, the efficiencies in EMS system not only determines the bill savings, but also influences the battery charging and discharging behaviours. When the energy price difference is small during the day, the battery system with low conversion efficiency could have limited /little benefit to customers.

3.6 Conclusion

In this chapter, a new EMS in a smart home to optimize battery storage's DSR behaviour is presented. A simplified problem formulation that model the whole system as a relationship between final energy cost and battery power is proposed. It considers and discusses the impact of different load profiles, different battery charge rate and conversion efficiency in EMS.

In detail, the key findings are as follows: 1) The results show that the proposed EMS effectively reduces the energy bill by 22%; 2) The battery control strategies can be greatly affected by load profiles. 3) Larger benefit will be brought in daytime high

demand customers using the battery and EMS given high price during the day. 4) The battery is less important in overnight high demand customers. 5) The increased battery charge rate could bring increased electricity bill savings. However, the incremental benefit will be reduced after reaching certain battery charge rate; 6) Within certain range of efficiencies, the EMS performance is the same for the customers. 7) In a given TOU, the unreasonable converter efficiencies limit the function of EMS. In order to make full use of the battery in shifting demand in the EMS system, the efficiencies should be set with the consideration of price differences. The results are useful for consumer homes of different load profiles to use energy storage, while taking advantage of local renewables and cheap central supply.

Chapter 4. Improved Problem Formulation for Optimal DSR in Hybrid AC/DC Systems

With the increasing penetration of DC appliances and LCTs, building a local DC network built at customers' premise would be an economical alternative for ensuring customer benefits. However, to achieve maximum DSR benefit, the increasing components including both AC/DC generations and loads largely could increase optimization problem scale and solution space. The piecewise function formulation proposed in the Chapter 3 could be a simplified but accurate solution to address this challenge.

Therefore, this chapter extends the piecewise function formulation to the hybrid AC/DC systems. The new formulation is built at the whole system level such that all power transfers between AC/DC or DC/AC are reflected in the ac power drawn from the main grid. The advantages of reducing the problem solving complexity and improves efficiency modelling accuracy are fully demonstrated. The proposed method will take full advantage of local DC network and TOU tariff to guarantee the maximum benefit of customers.

4.1 Introduction

With the wide-spread deployment of electronic devices at homes and commercial premises, more DC devices are connected to the distribution networks. Apart from the converter-based computers/laptops, there will be increasing penetration of DC powered low carbon technologies (LCTs) available, such as PV, batteries (including electric vehicles (EVs)), light-emitting diode (LED).

A significant amount of research integrated DC powered LCTs in DSR strategies' designing. However, most studies [73, 88-97] were concentrated on either AC system or DC system. The optimal conversion power between AC and DC system was not considered. Several studies [73, 88-95] connected these DC appliances to the AC system with individual AC-DC converters. Day-ahead and short-term (hourly ahead) optimal battery dispatching schedules of grid-connected PV were proposed in [73, 88-91] using linear programming, dynamic programming, genetic algorithm, Lagrangian relaxation-based optimization algorithm and quadratic optimization respectively. In [92], the uncertain behaviours of PV system were considered and the energy management strategies derived from stochastic dynamic programming were compared

with that derived from the rule-based system. Authors in [93] used robust mix integer linear programming (MILP) to develop the optimal control strategies of the battery. Many literatures took EV as battery: a heuristic method of EV charging and an optimal EV charging was used as demand response in [94] and [95] respectively. On the other hand, studies [96, 97] only considered DC networks: to assure reliability and efficiency by electronic loads and PV with optimization [96], or to reduce energy cost by EV with rule-based decision-making model [97].

With the increasing domestic DC and AC demand and supply, more hybrid AC/DC system will be formed by connecting a new DC network to the original AC system. Thus, it consists at least four parts, DC generation, DC load, AC load and AC generation (or main grid). It is more energy efficient and cost-effective by eliminating unnecessary AC/DC conversion losses. The majority of the literature concentrated on design control strategies [79, 98-100] to increase the operation reliability of hybrid AC/DC system.

However, in the hybrid AC/DC system, the conversion power between AC and DC system, i.e. the multiple power transfers between DC generation, DC load, AC load and AC generation (or main grid), needs further consideration. The transferred power with different directions has different conversion efficiencies, and thus the optimal power interaction within hybrid AC/DC system is more complicated. A study in [101] proposed an energy management model in AC/DC micro-grid. Its optimization formulation was built from a component level that enumerates power exchange between components, i.e. large numbers of variables and constraints were used to differentiate power in different directions, such as battery input and output power, AC-to-DC and DC-to-AC power and home-to-grid and grid-to-home power. The large number of variables and constraints increase the difficulty in finding the optimal solution. Yet, few other studies so far have focused on optimal DSR in such hybrid AC/DC system particularly.

This chapter extends the formulation proposed in the last chapter –piecewise function formulation to determine optimal AC and DC power usage in local hybrid AC/DC system for DSR. Instead of building the formulation from a component level, this new formulation is built at the whole system level such that all power transfers within AC/DC system are reflected in the AC power drawn from the main grid. In detail, the AC power drawn from the main grid is represented as piecewise functions of local DC

power. Different AC and DC power relationships are reflected in different piecewise function segments, i.e. different conversion efficiencies are represented as different slopes. The piecewise functions are then converted to 0-1 integer model and directly resolved by MILP. The approach is applied to a school, in the UK, which has large differences in demand over time, to assessing its feasibility and investigating the performance of DSR with the incentive of time of use (TOU) tariffs. Additionally, the impact of conversion efficiency on control strategy design and benefits receiving is discussed.

The main contribution of this chapter is a new piecewise function problem formulation for optimizing power transfer within the hybrid AC/DC system, and between local and the central grid. It significantly reduces complexity in optimization by substantially reducing the number of variables/constraints and searching space, and also extends modelling capability for converter efficiency by building in the power-related converting efficiency.

The rest of chapter is organized as follows: Section 4.2 introduces the local hybrid AC/DC network; Section 4.3 proposes the optimization model; Section 4.4 develops a piecewise function formulation to represent AC and DC power; Section 4.5 demonstrates practical case studies and compare the model with traditional model and Section 4.6 draws the conclusion.

4.2 Local hybrid AC/DC network

An example of a local hybrid AC/DC network is shown in figure 4-1. The whole system can be classified to AC system and DC system. A DC bus is built to connect the DC powered devices and linked to the AC system by a bi-directional converter. It includes four parts: DC generation (PV), DC load (LEDs, computer and battery), AC load and the main grid. This structure enables the direct use of the PV output by battery and DC loads prior to it being converted to AC through an export inverter. It increases the energy use efficiency by eliminating the unnecessary AC/DC converting losses. Additionally, the supply reliability will be increased since the AC and DC loads in the system are flexibly supplied by both AC and DC sources. This system is implemented

in the project Sola Bristol [59].

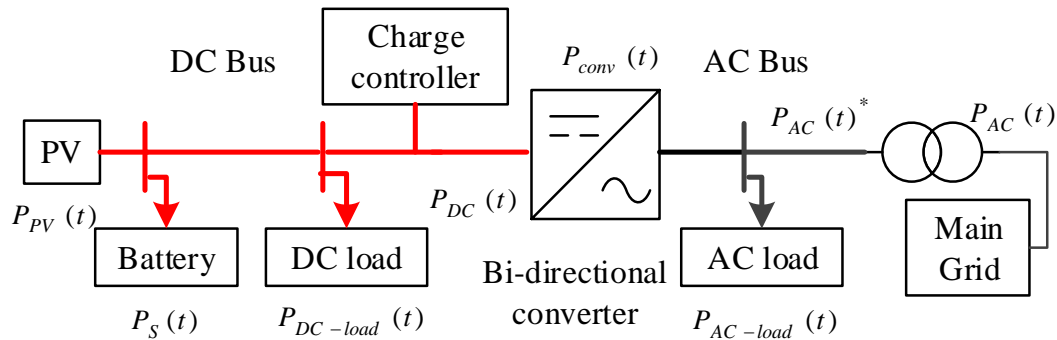


Figure 4-1 Overview structure of a local hybrid AC/DC system

However, on the other hand, the different types of demand and supply bring complex relationship of interacted power between DC generation, local DC demand, local AC demand and main grid. There should be more sophisticated energy management approach to handling the issues on optimal AC and DC power usage considering converting efficiency.

4.3 Optimization model of energy management system

4.3.1 Overview of the Energy Management System

Similar with the EMS proposed in the last chapter, an example structure of EMS used in local hybrid AC/DC networks to facilitate DSR is shown in figure 4-2. It is responsible for: 1) reading forecasted customer load data, PV output and TOU tariffs; 2) generating battery charging and discharging schemes and converter operation schemes; 3) controlling charge controller and bi-directional converter to achieve the needed state of charge (SoC) of the battery. This study focuses on developing optimal battery charging and discharging schemes and converter operation schemes particularly. The schemes are developed and set in advance, before the beginning of a day.

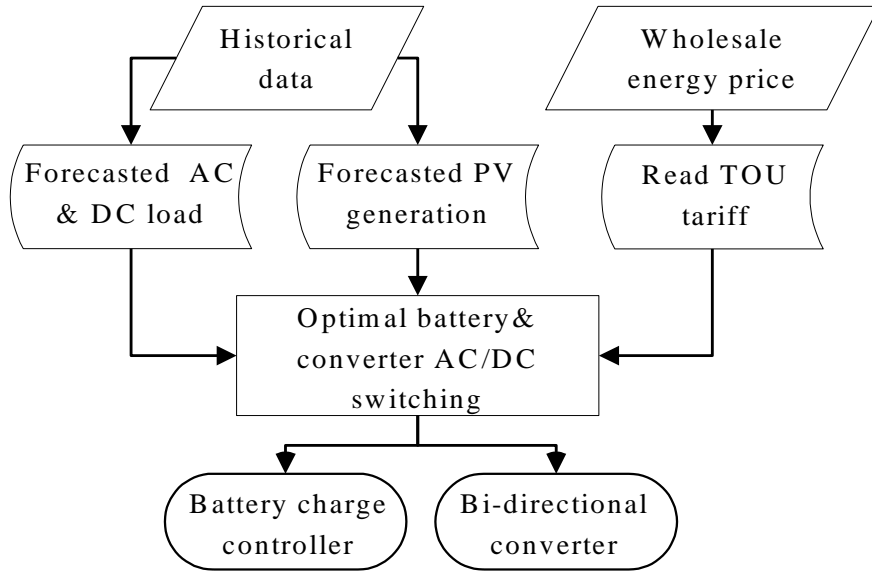


Figure 4-2 Energy management system

4.3.2 Optimization model

To optimize its operation in hybrid AC/DC system, the power transfers between all the components need to be modelled, i.e. the power transfer between the battery, PV, DC and AC load, and main grid. Additionally, the different power transfer efficiencies should be considered. Therefore, it is relatively complicated to model a hybrid AC/DC system and optimize its power transfers.

The daily battery and converter operation algorithm is designed to optimize the AC and DC power usage with minimum electricity cost under TOU tariffs. The constraints come from the battery and converter devices and power balance.

A. Objective

The objective is to minimize the cost of purchasing electricity from the main grid. In this model $T=0.5h$.

$$\text{Min} \sum_{t=1}^{48} C(t)P_{AC}(t)^*T \quad (4-1)$$

$$C(t)P_{AC}(t)^* = \begin{cases} U(t)P_{AC}(t) & \text{if } P_{AC}(t) \geq 0 \\ S(t)P_{AC}(t) & \text{if } P_{AC}(t) < 0 \end{cases} \quad (4-2)$$

Where, $C(t)$ is the energy price at time t . $P_{AC}(t)^*$ is the AC power transfer between customer and main grid at time t . $U(t)$ is TOU rate at time t . $S(t)$ is the power selling

price at time t . $P_{AC}(t)$ is customer (needed) AC power at time t . Similar with the last chapter, it is assumed that selling electricity price is zero because there is no local energy market. Therefore $S(t) = 0$.

- AC power

The needed AC power is the sum of original AC demand and converted DC demand, as shown in equation 4-3. DC demand is converted to AC form in calculating costs, because only AC systems carry the information of costs in this system. During the converting process, AC-to-DC and DC-to-AC conversion efficiencies are considered in equation 4-4. Where, $\eta_{D/A} = 1/\eta_{A/D}$.

$$P_{AC}(t)^* = P_{AC-load}(t) + P_{conv}(t) \quad (4-3)$$

$$P_{conv}(t) = \begin{cases} \eta_{A/D} P_{DC}(t) & \text{if } P_{DC}(t) > 0 \\ 0 & \text{if } P_{DC}(t) = 0 \\ \eta_{D/A} P_{DC}(t) & \text{if } P_{DC}(t) < 0 \end{cases} \quad (4-4)$$

Where, $P_{AC-load}(t)$ is the customer's AC load at time t . $P_{conv}(t)$ is the AC demand converted from DC demand at time t . $P_{DC}(t)$ is DC power/demand at time t . $\eta_{A/D}$ and $\eta_{D/A}$ are AC-to-DC and DC-to-AC conversion efficiencies.

- DC power

DC demand is the sum of DC load, battery input and minus PV output.

$$P_{DC}(t) = P_{DC-load}(t) + P_S(t) - P_{PV}(t) \quad (4-5)$$

Where, $P_{DC-load}(t)$ is DC load at time t . $P_{PV}(t)$ is PV output at time t . $P_S(t)$ is the battery power. Battery is taken as DC load, when the battery charges, $P_S(t) > 0$; when discharges, $P_S(t) < 0$; when battery is idle, $P_S(t) = 0$. It should be clarified that only the efficiency of the AC/DC converter is considered as this is the dominate efficiency factor in the AC/DC system.

In this model and battery efficiency is taken as 100%, because generally, the used Li-ion battery is considered to have higher efficiency (near 100%) [102]. We follow the similar assumption that the battery losses are negligible in formulating local hybrid

AC/DC networks.

B. Constraints

The constraints of devices and power balance should be satisfied, and are the same as proposed in the last chapter, which are:

- Constraints of devices

Battery charging and discharging rates should be within certain ranges, which are constrained by its physical properties as in equation 4-6. The amount of energy stored in the battery is limited as shown in equations 4-7 and 4-8. The initial energy storage in the battery is set at its minimal limit, i.e. $E(0) = E(48) = E_{min}$. In equation (4-7), the energy stored in the battery for other time slots are constrained.

$$P_D^{max} \leq P_S(t) \leq P_C^{max} \quad (4-6)$$

$$E_{min} \leq E(t) \leq E_{max}, \quad t = 1, 2, \dots, 47 \quad (4-7)$$

$$\begin{cases} E(t) = E(t-1) + \Delta E(t) & t = 1, 2, \dots, 48 \\ \Delta E(t) = P_S(t)T \end{cases} \quad (4-8)$$

Where, P_D^{max} and P_C^{max} are the maximum discharging and charging rates. $E(t)$ is the stored energy in the battery at time t . E_{min} and E_{max} are the minimum and maximum battery stored energy. $\Delta E(t)$ is the energy change in the battery at time t .

Different from previous case, the converter in this model converts the power of PV, battery and DC load. The converting power should be within the converter rating power.

$$-R \leq P_{conv}(t) \leq R \quad (4-9)$$

Where R is the converter rating power.

- Constraints of power balance

The sum of charging and discharging power of one day is assumed to be zero:

$$\sum_{t=1}^{48} P_S(t) = 0 \quad (4-10)$$

4.3.3 Model discussion

As shown in equations 4-2 to 4-5, in this hybrid AC/DC system, there can be multiple power transfers/conversions between AC/DC generation, demand and energy storage. Previous problem formulations for optimizing such energy systems are built at the component level, each power transfer along each direction at each time slot is represented by its unique variables and its constraints, the whole system energy management will enumerate power exchanges across all components over 24 hours period. However, these traditional problem formulations, which will be discussed in section 4.4.4 in detail, have two main disadvantages:

- The number of variables in the traditional formulation will be doubled, and the system state and searching space in the optimization exponentially increased with increased components and over increased time period. Thus, substantially increase the difficulty for optimizing the power transfers across the system.
- In traditional formulation, efficiencies, $\eta_{A/D}$ and $\eta_{D/A}$, are taken as a constant value, which simplified the formulation but sacrifice significant modelling accuracy given the wide-range of conversion efficiency exists across the broad operational regions.

This chapter extends the previously proposed piecewise function problem formulation to overcome these two disadvantages. This new formulation simplifies the representation of all power transfers between batteries and local AC/DC network, between local AC/DC network and the main grid. Additionally, the proposed formulation can consider power-related converting efficiency.

4.4 Problem formulation

In the proposed model, the relationship of AC and DC power is built by piecewise

functions for each time slot. The piecewise functions are then converted to mixed integer model which is resolved by MILP.

4.4.1 Building of piecewise function

The steps of building piecewise function in hybrid AC/DC model are similar with that in chapter 3. In the hybrid AC/DC system, piecewise functions are built to represent AC and DC demand relationship. In detail:

- **Linearization:** Based on equations 4-2 and 4-3, at each time slot, the AC power drawn from the main grid is the sum of needed AC power and converted DC demand. Therefore, electrical power purchased from the main grid, $P_{AC}(t)$, is a linear function of converted DC demand, $P_{conv}(t)$.
- **Enumeration:** Based on equations 4-2 to 4-4, there are different ratios of AC and DC power in the two different scenarios that local hybrid AC-DC system would face: 1) AC system supplies DC bus: when $P_{DC}(t) > 0$ and the ratio (efficiency) is $\eta_{A/D}$; 2) DC bus supplies local AC demand without sufficient power: when $P_{DC}(t) < 0$ and the ratio (efficiency) is $\eta_{D/A}$.

The example of a built piecewise function in the Cartesian Coordinates is shown in figure 4-3. Y-axis, $P_{AC}(t)$, represents the electrical power purchased from the main grid; and x-axis, $P_{DC}(t)$, is the DC power in the home. Different segments match different scenarios: 1) the curve in the first quadrant in the Cartesian Coordinates means that AC system supplies DC bus and DC power is represented as positive; 2) the curve in the second and third quadrants, it means DC bus supplies AC system and the decreasing DC power is represented as negative.

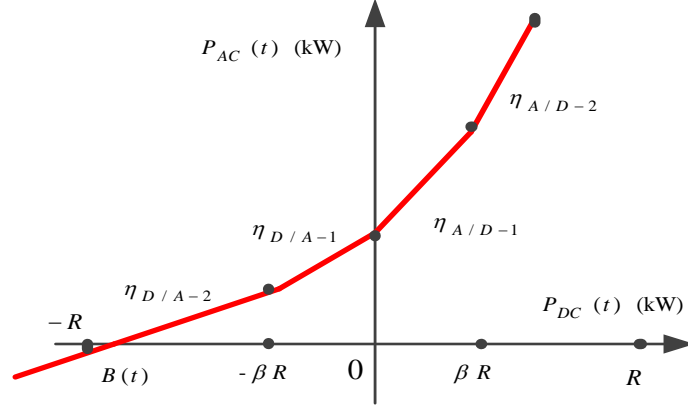


Figure 4-3 Demand representation in the hybrid AC/DC system

A. The slopes of the piecewise functions

In piecewise functions of hybrid AC/DC system, different slopes in different segments represent the AC-to-DC conversion efficiencies, $\eta_{A/D}$, DC-to-AC conversion efficiencies, $\eta_{D/A}$. When AC power supplies DC load (AC-to-DC efficiencies), the slope of is greater than 1, i.e. $\frac{P_{AC}(t)}{P_{DC}(t)} > 1$, since part of AC power becomes conversion losses; When DC power supplies AC load (DC-to-AC efficiencies), the slope is less than 1, i.e. $\frac{P_{AC}(t)}{P_{DC}(t)} < 1$, since part of DC power becomes conversion losses.

By changing the number of slopes, the proposed formulation can model any numbers of efficiencies. The efficiency verses converted power of the AC/DC converter is shown in the figure below. The converter efficiency modelling accuracy is increased by building more practical power related conversion efficiencies into the formulation. In this study, two power-related efficiencies are considered in the formulation because of the price difference impacts, which will be illustrated in detail in the section D. If AC system supplies DC bus with less than β of converter rating power, βR , the efficiency is $\eta_{A/D-1}$; else the efficiency is $\eta_{A/D-2}$. Similarly, when the DC bus supplies local AC demand, the efficiencies are $\eta_{D/A-1}$ and $\eta_{D/A-2}$ respectively. It should be noted that there is no obstacle to extend the current model to more efficiencies in the optimization model.

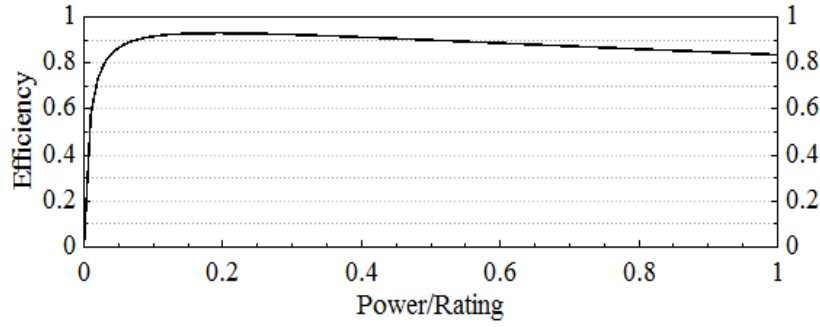


Figure 4-4 Converter efficiency

B. The breakpoints of piecewise functions

The breakpoints of piecewise function are determined by original AC load, $P_{AC-load}(t)$, DC-to-AC conversion efficiencies, $\eta_{D/A}$, $\eta_{D/A-1}$, $\eta_{D/A-2}$, and constraints of devices.

Two of the breakpoints are the crossing points of curve and x-y axes, $P_{AC-load}(t)$ and $B(t)$. Particularly, $B(t)$, is determined by original AC demand, DC-to-AC conversion efficiencies and converter rating as shown in equation 4-11.

$$\begin{cases} B(t) = -(P_{AC-load}(t) - \beta R \eta_{D/A-1}) / \eta_{D/A-2} & \text{If } P_{AC-load}(t) > \beta R \\ B(t) = -P_{AC-load}(t) / \eta_{D/A-1} & \text{If } P_{AC-load}(t) \leq \beta R \end{cases} \quad (4-11)$$

Where, β is the coefficient determines conversion efficiency boundary. The rest breakpoints are determined by the capacity of the converter: R , $-R$, βR and $-\beta R$.

C. The value range of piecewise functions

The DC power range is determined as the minimum available range considering both battery and converter power limit. In detail, the minimum and maximum power on the DC bus is derived by 1) converting the battery charge and discharge rates limits to DC power limits on the DC bus as shown in equation 4-12; 2) comparing the converted battery power limits and the converter rate limit as shown in equations 4-13 and 4-14.

$$\begin{cases} P_{S-DC}^{min}(t) = P_D^{max} + P_{DC-load}(t) - P_{PV}(t) \\ P_{S-DC}^{max}(t) = P_C^{max} + P_{DC-load}(t) - P_{PV}(t) \end{cases} \quad (4-12)$$

$$\begin{cases} P_{DC}^{min}(t) = \max [P_{S-DC}^{min}(t), -R] \\ P_{DC}^{max}(t) = \min [P_{S-DC}^{max}(t), R] \end{cases} \quad (4-13)$$

$$P_{DC}^{min}(t) \leq P_{DC}(t) \leq P_{DC}^{max}(t) \quad (4-14)$$

The piecewise function of each time slot is built after defining slopes, breakpoints and the DC bus power range. For each time slot, the piecewise function of $P_{AC}(t)$ might range from four segments to one segment, which is determined by the values of break points, $B(t)$, R , $-R$, βR and $-\beta R$, and DC power range, $[P_{DC}^{min}(t), P_{DC}^{max}(t)]$.

D. Adding price information to piecewise functions

The price information can be added to piecewise functions as coefficients of AC power, $P_{AC}(t)^*$. Since it is assumed that selling price is zero, $S(t)P_{AC}(t) = 0$, when $P_{AC}(t) < 0$. The piecewise function of $C(t)P_{AC}(t)^*$ at the third quadrant becomes zero and overlaps with x-axis. Therefore, for each time slot, the new piecewise function of $C(t)P_{AC}(t)^*$ might range from five segments to one segment, which is determined by the values of break points, $B(t)$, R , $-R$, βR and $-\beta R$, and DC power range $[P_{DC}^{min}(t), P_{DC}^{max}(t)]$. One example of five segments piecewise function is shown in figure 4-5.

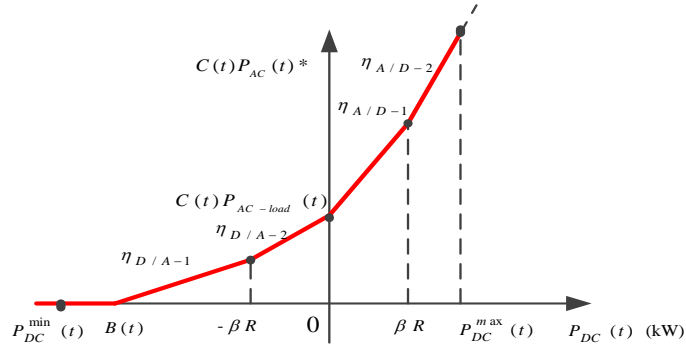


Figure 4-5 Piecewise function of energy cost and DC power

4.4.2 Conversion of piecewise function into mixed integer model

The piecewise function conversion process is the same with that in chapter 3. The only difference is that the battery power in the previous model is changed to DC power in this model. The piecewise functions are converted into a mixed integer model by virtual variables: $w_n(t)$ and $z_n(t)$.

Since the segment number is increased, the virtual variable number is increased correspondingly. There might be five segments, therefore, m might be 6 in this model. The mathematical representation is:

$$\begin{cases} \sum_{n=1}^{m-1} z_n(t) = 1 & (m = 2,3,4,5,6) \\ z_n(t) = 0 \text{ or } 1 \end{cases} \quad (4-15)$$

$$\begin{cases} \sum_{n=1}^m w_n(t) = 1 & (m = 2,3,4,5,6) \\ w_n(t) \geq 0 \end{cases} \quad (4-16)$$

$$\begin{cases} w_n(t) \leq z_n(t) & \text{if } n = 1 \\ w_n(t) \leq z_{n-1}(t) & \text{if } n = m \\ w_n(t) \leq z_{n-1}(t) + z_n(t) & \text{else} \end{cases} \quad (4-17)$$

In detail, the DC bus power, $P_{DC}(t)$ is represented by virtual variables, $w_n(t)$ and values of breakpoints on x-axis, $D_n(t)$.

$$P_{DC}(t) = \sum_{n=1}^m D_n(t)w_n(t) \quad (m = 2,3,4,5,6) \quad (4-18)$$

$$D_n(t) \in [P_{DC}^{min}(t), B(t), -\beta R, 0, \beta R, P_{DC}^{max}(t)]$$

The cost of electricity, $C(t)P_{AC}(t)^*$ is also represented by virtual variables, $w_n(t)$

and values of breakpoints on x-axis, $A_n(t)$.

$$C(t)P_{AC}(t)^* = \sum_{n=1}^m A_n(t)w_n(t) \quad (m = 2,3,4,5,6) \quad (4-19)$$

$$\frac{A_n(t)}{C(t)} \in [0, P_{AC}(P_{DC}^{min}), P_{AC}(-\beta R), P_{AC-load}, P_{AC}(\beta R), P_{AC}(P_{DC}^{max})]$$

According to equation 4-5 and 4-18, the battery power, $P_S(t)$, can be replaced by $w_n(t), P_S(t) = F(w_n(t))$.

The final optimization model can be represented as:

A. Objective

$$\text{Min} \sum_{t=1}^{48} \sum_{n=1}^m A_n(t)w_n(t)T \quad (m = 2,3,4,5,6) \quad (4-20)$$

B. Constraints

$$\begin{cases} \sum_{t=1}^{48} \sum_{n=1}^m w_n(t) = 1 \quad (m = 2,3,4,5,6) \\ w_n(t) \geq 0 \end{cases} \quad (4-21)$$

$$\begin{cases} w_n(t) \leq z_n(t) \text{ if } n = 1 \\ w_n(t) \leq z_{n-1}(t) \text{ if } n = m \\ w_n(t) \leq z_{n-1}(t) + z_n(t) \text{ else} \end{cases} \quad (4-22)$$

$$\begin{cases} \sum_{t=1}^{48} \sum_{n=1}^{m-1} z_n(t) = 1 \quad (m = 2,3,4,5,6) \\ z_n(t) = 0 \text{ or } 1 \end{cases} \quad (4-23)$$

$$E_{min} \leq E(0) + \sum_{t=1}^{47} F(w_n(t)) * T \leq E_{max} \quad (4-24)$$

$$\sum_{t=1}^{48} F(w_n(t)) = 0 \quad (4-25)$$

As a result, the piecewise function is converted to 0-1 integer linear model with $A_n(t), D_n(t), w_n(t), z_n(t)$. The battery and converter operation schemes can be directly resolved by MILP.

4.4.3 Process of optimization problem-solving

In summary, the steps of piecewise function formulation and solving are illustrated in figure 4-6. In details, the steps are:

- i) Develop the piecewise function for time t with conversion efficiencies, $P_{AC-load}(t)$, converter capacity and calculate DC bus power constraints with $P_{DC-load}(t), P_{PV}(t)$, converter capacity.
- ii) Convert piecewise function into mixed integer model with the virtual variables, $w_n(t)$ and $z_n(t)$.
- iii) Assess whether the electricity bill piecewise functions of the whole day have been built or not.
- iv) Add power balance constraints into the mixed integer model with the virtual variables, $w_n(t)$ and $z_n(t)$.

- v) Solve the objective function with global optimization by revised simplex method and branch-and-bound algorithm.
- vi) Post-process the optimal results by converting the results of virtual variables $w_n(t)$ and $z_n(t)$ back to $P_{DC}(t)$.
- vii) Calculate the battery input and output $P_S(t)$ and optimization objective.

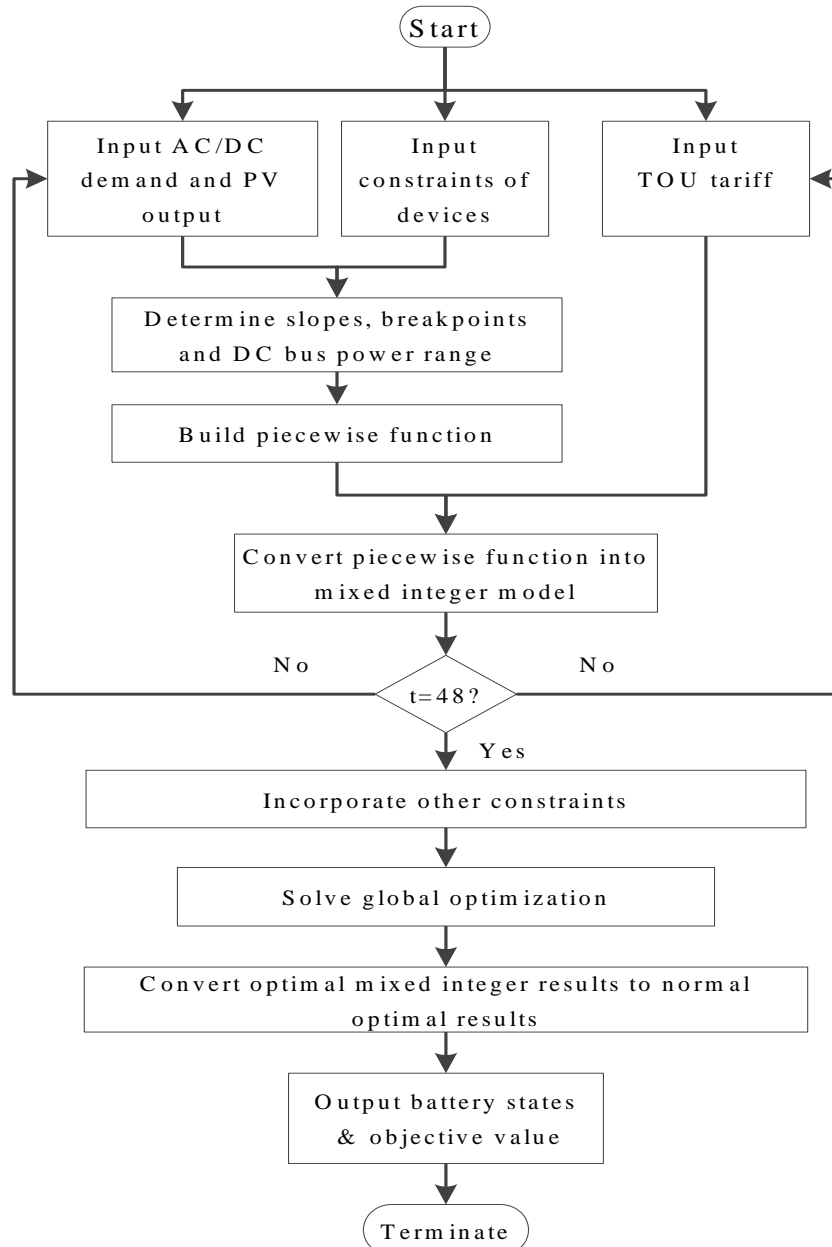


Figure 4-6 Flowchart of optimization problem-solving

4.4.4 Formulation discussion

The advantages of the piecewise function formulation are: 1) it reduces the variables and constraints in the optimization process; 2) it extends modelling capability for converter efficiency.

The limitation of the proposed formulation is discussed in the section C.

A. Reducing complexity of optimization

The piecewise function formulation not only reduce the number of variables and constraints, but also significantly reduce the solution space (searching space) in the optimization process compared with the traditional component level formulation.

- The number of variables and constraints

Traditional formulation using MILP doubles the original numbers of variable and increases the constraints correspondingly in order to differentiate power flow directions and conversion efficiencies. Traditional battery scheme optimization formulations, such as [93, 103, 104], differentiate the charge and discharge power and adds on the coefficients of integer 0 and 1 respectively. When extending the model to the proposed hybrid AC/DC system, not only the battery input/output power but also the AC-to-DC/ DC-to-AC power and main grid-to-hybrid/hybrid-to-main grid the power should be split with coefficients 0 and 1 [101] as shown in equations 4-26 to 4-28. At each time slot, there are 3 pairs of 0-1 integer variables: $X_c - X_D$, $X_{AC-DC} - X_{DC-AC}$ and $X_{M-H} - X_{H-M}$. If battery efficiency is not considered, there are 2 pairs of 0-1 integer variables: $X_{AC-DC} - X_{DC-AC}$ and $X_{M-H} - X_{H-M}$. As a result, in each time slot, the number of variables is 9, including 4 original AC/DC and home/main grid variables, 4 integer variables and battery power.

$$\begin{cases} P_S(t) = X_c P_c(t) + X_D P_D(t) \\ X_c + X_D = 1 \end{cases} \quad (4-26)$$

$$\begin{cases} P_{conv}(t) = X_{AC-DC} P_{AC-DC}(t) + X_{DC-AC} P_{DC-AC}(t) \\ X_{AC-DC} + X_{DC-AC} = 1 \end{cases} \quad (4-27)$$

$$\begin{cases} P_{AC}(t) = X_{M-H}P_{M-H}(t) + X_{H-M}P_{H-M}(t) \\ X_{M-H} + X_{H-M} = 1 \end{cases} \quad (4-28)$$

By contrast, the proposed formulation reduces the variables and constraints in the optimization process. The number of variables in piecewise function formulation, $w_n(t), z_n(t)$, is proportional to segments number. The number of integer variables, $z_n(t)$, is equal to segments number. The number of non-integer variables, $w_n(t)$, is equal to segments number plus one. If considering constant AC-to-DC and DC-to-AC efficiencies, $\eta_{A/D}, \eta_{D/A}$, which is the same with the traditional formulation, the maximum segments number of piecewise functions is 3 (if selling price is zero) or 2 (if selling price is not zero) at each time slot, as shown in figure 4-7. As the DC power range, $[P_{DC}^{min}(t), P_{DC}^{max}(t)]$, changes at each time slot, the piecewise function might be one or two segments. As a result, at each time slot, the number of variables ranges from 7(=2×3+1) to 1, when selling price is zero, or 5(2×2+1) to 1 when the selling price is not zero. Assuming the time slot number is k, the comparison on variable number and constraints is shown in table 4-1.

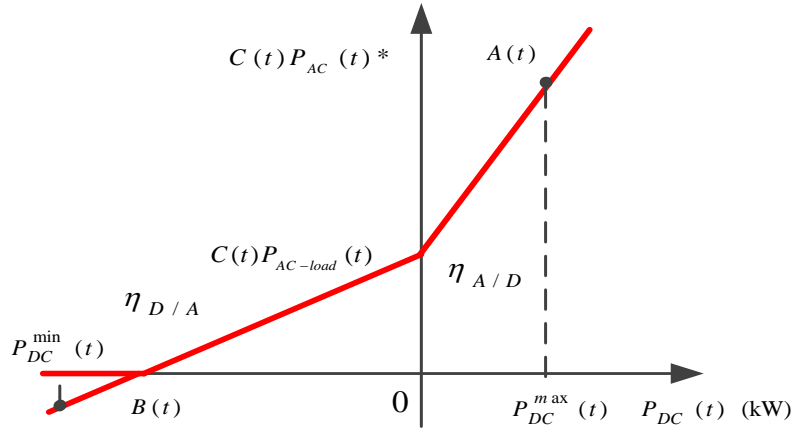


Figure 4-7 Demand representation with constant converter efficiency

Table 4-1 Variable and constraints number comparison

Formulation	Traditional formulation		
Condition	$S(t) = 0$ & $S(t) \neq 0$	$S(t) = 0$	$S(t) \neq 0$
Variable number at t	9×k	[k,7×k]	[k,5×k]
Constraints number at t	10×k	[2×k, 8×k]	[2×k,6×k]

- Solution space

The variable number influences the solution space and complexity of solving the optimization problem. In this study, “branch and bound” method is used. The problem is firstly solved by linear programming, then integer variables are processed until all proper integers found with minimum/maximum objective. Traditional formulation has larger solution space to search due to more binary variables and the permutation and combination. As shown in table 4-2, for k time slots calculation, the test scenarios will be $4 \times k$. For the optimization process in this study, as for 48 time slots of 24 hours, the final test number of scenarios is 192 ($=4 \times 48$). To find the optimal solution, calculation can be conducted 4^{48} times.

However, in piecewise function formulation, the solution space at each time equals to the number of binary variables, which reduce the possible scenarios of calculation. Therefore, when selling price is zero, the final maximum scenario (solution space) is 144($=3 \times 48$) and when selling price is not zero, the maximum scenarios is 96($=2 \times 48$). The minimum scenario for both case is 48($=1 \times 48$). In order to find the optimal solution, calculation can be conducted between 48 times to 3^{48} times.

Table 4-2 Solution space comparison

Formulation		Traditional formulation		Piecewise function formulation				
Condition		$S(t) = 0$ & $S(t) \neq 0$		$S(t) = 0$			$S(t) \neq 0$	
Time	System state	X_{AC-DC}	X_{M-H}	z_1	z_2	z_3	z_1	z_2
t_1	1	0	0	0	0	1	0	1
	2	0	1	0	1	0	1	0
	3	1	0	1	0	0	-	-
	4	1	1	-	-	-	-	-
t_2	1	0	0	0	1	-	1	-
	2	0	1	1	0	-	-	-
	3	1	0	-	-	-	-	-
	4	1	1	-	-	-	-	--
...	
t_{48} (t_k)	1	0	0	1	-	-	1	0
	2	0	1	-	-	-	0	1
	3	1	0	-	-	-	-	-
	4	1	1	-	-	-	-	-
Total solution space number		192 ($4 \times k$)		[48,144] ($[k, 3 \times k]$)			[48,96] ($[k, 2 \times k]$)	
Possible solution number		4^{48} (4^k)		[48, 3^{48}] ($[k, 3^k]$)			[48, 2^{48}] ($[k, 2^k]$)	

B. Extending converter efficiency modelling capability

The piecewise function formulation could be built with more power related conversion efficiencies, which, is more practical in simulating the real condition and more accurate to model the converter efficiencies.

The real efficiency of the converter is power related as shown in figure 4-8. The conversion efficiency decreases from 93% to 83% with the converting power increase. The study [73] simulates the non-linear converter efficiency using quadratic interpolation from experimental derived curves. Incorporating the non-linear converter efficiency leads to a non-linear optimization problems, which are inherently much more difficult to optimize than linear problems [105]. Therefore, when linearizing the non-linear problem brings limited adverse effect to the results, linear programming is preferred. For example, when the converter efficiency of the AC/DC converter is high or the converted power is low. The previous optimization

formulations set conversion efficiency as a constant. However, the accuracy-reduced efficiency representation will bring different effects to the final customer savings. Whether there is no effect or significant reduced bill savings is depended on price signals,

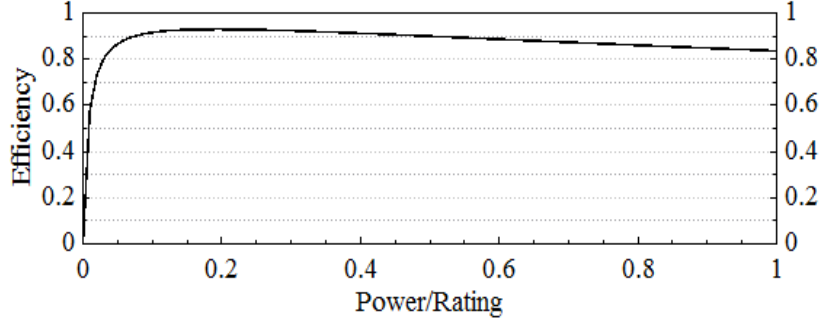


Figure 4-8 Converter efficiency

In the optimization model, there is interacted relationship between conversion power and conversion efficiency. The converted power increase leads to conversion efficiency decrease. However, when the conversion efficiency decreases to a “lowest” limit, the conversion power will be forced to zero in the optimization. The reason for the latter is that the cost in conversion losses is equal or larger than the benefit in price incentive demand shifting and reduction. Given the tariff, the “lowest conversion efficiency” is calculated as equations 4-29 to 4-31:

The customer saving equals the benefit of selling electricity at high price minus the cost of buying the electricity at low price:

$$Saving = P_2 \eta_{D/A} (E_{AC} + E_{re}) - P_1 \eta_{A/D} E_{AC} \quad (4-29)$$

Where, P_1 and P_2 are the low and high prices, E_{AC} is the shifted AC energy, E_{re} is the PV output to AC system in high price.

Set $Saving \geq 0$. By rearranging equation 4-25, a relationship of the conversion efficiencies, price ratio and energy can be provided:

$$\frac{\eta_{D/A}}{\eta_{A/D}} = \eta_{D/A}^2 \geq \frac{P_1}{P_2} \left(1 - \frac{E_{re}}{E_{AC} + E_{re}} \right) \quad (4-30)$$

Given $\left(1 - \frac{E_{re}}{E_{AC} + E_{re}} \right) \leq 1$:

$$\frac{\eta_{D/A}}{\eta_{A/D}} = \eta_{D/A}^2 \geq \frac{P_1}{P_2} \geq \frac{P_1}{P_2} \left(1 - \frac{E_{re}}{E_{AC} + E_{re}}\right) \quad (4-31)$$

When only consider the AC demand shifting or there is no surplus PV output converted to AC system, i.e. $E_{re} = 0$ and $\left(1 - \frac{E_{re}}{E_{AC} + E_{re}}\right) = 1$, the “lowest conversion efficiency” will be $\frac{P_1}{P_2}$.

If the conversion efficiency is greater than the square root of the low and high price ratio, AC demand shifting is allowed in the optimization process, since the benefit is larger than the conversion cost. Otherwise, either only DC to AC direction power flow is allowed due to PV output compensating or separate DC and AC system operation is allowed to reduce cost in conversion losses. For different price steps in TOU tariff, there are different “lowest conversion efficiencies”. The relationship between “lowest conversion efficiencies” and price ratio is shown in figure 4-9. The used TOU tariffs are derived from the wholesale energy price of Great Britain (GB) [106]. The examples of winter and summer are shown in figure 4-10.

Whether the higher price is suitable for demand shifting depends on the conversion efficiency. The wholesale energy price indicates that in the real world, there will be a small price difference between the TOU price steps, such as the difference between low and shoulder price in winter weekday. The price ratio of low and shoulder price, $r = \frac{P_1}{P_2}$, in winter weekday is 0.822. Based on equation (4-29)-(4-31), the calculated lowest conversion efficiency is 90.6% shown in figure 4-8. It indicates that the AC demand shifting at shoulder price with lower than 90.6% efficiency will waste money.

The previous optimization formulation cannot differentiate the efficiencies and amount of AC demand shifting. If the constant conversion efficiency is set greater than 90.6%, the large AC demand shifting during shoulder price actually brings cost in energy loss. Otherwise, if the conversion efficiency is set less than 90.6%, there will be no AC demand shifting during shoulder price.

Given this condition, it is important to introduce power-related efficiency into problem formulation. The proposed piecewise function formulation could build with different conversion efficiencies across different operating range. By using multiple

constant efficiencies in the model and solving it with linear programming, the proposed formulation can not only guarantee maximum customer benefits but also simplify the optimization. Thus, the optimization process could avoid a large amount of AC demand shifting (with low conversion efficiency) in shoulder price time and set a small amount of AC demand shifting with efficiency larger than 90.6%. According to figure 4-9, when the converting power is less than $0.5R$, the efficiency is higher than 90.6%. Therefore, in the piecewise function formulation, the breakpoints of two efficiencies, βR , could be set as $0.5R$ under this TOU price condition.

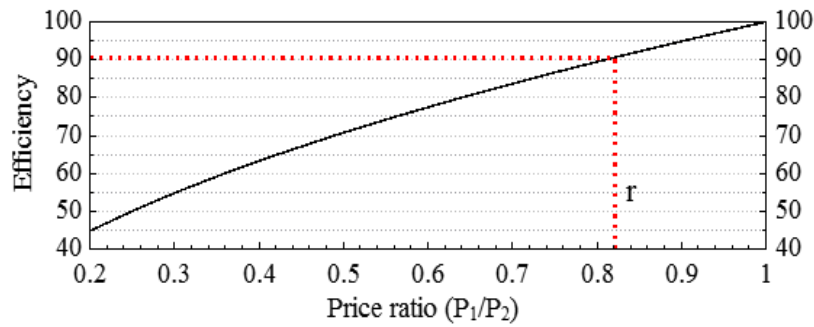


Figure 4-9 Relationship between efficiency and price ratio

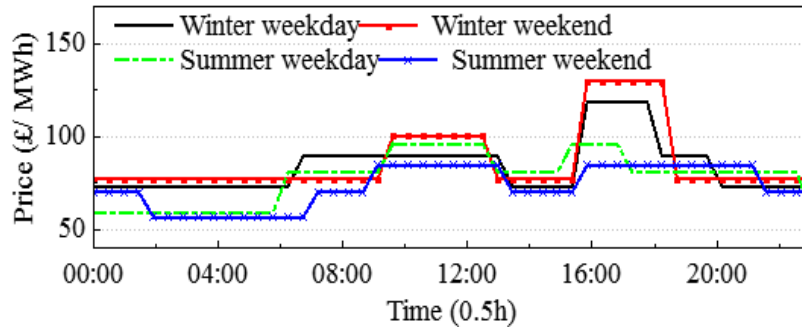


Figure 4-10 TOU tariffs

C. Formulation limitation

In the piecewise function formulation, only the AC/DC conversion efficiency is represented in the slope of the piecewise function. However, the conversion efficiency within local DC network is neglect. In detail, the DC load and generation is summarized as DC power and represented in the X-axis. The battery charge and discharge losses cannot be reflected in the DC power representation in the piecewise function formulation.

If the battery efficiency is considered, the two-step piecewise function formulation could be used. The first step is to model the relationship between DC power and

battery power as shown in the chapter 3. The battery input and output efficiencies are represented as piecewise function slopes in the formulation. The second step is to input the battery model into the AC/DC power exchange model. However, two levels of piecewise functions create complex model and large number of variables, which contradict to the initiative of the piecewise function formulation. Considering the Li-ion battery has the high efficiency, the piecewise function formulation for hybrid AC/DC system do not takes battery efficiency into consideration. Alternatively, the battery and converter efficiencies could be combined as one efficiency and represented as the slope of the piecewise function to calculate the benefit of the EMS system.

4.5 Demonstration

4.5.1 System specification

The proposed hybrid AC/DC system DSR strategy is applied to a primary school in Bristol, UK. The schools have both high AC and DC demand/supply and the demand significantly varies across term and holiday time. Winter and summer are selected as typical seasons for analysis.

The selected typical AC load in both term time and holidays are shown in figure 4-11. The peak demand in winter term weekday is 21kW, which is twice as much as that in summer term weekday (10kW). Additionally, both winter and summer holidays, including weekends and off-term weekday, have very smaller demand with the peak of 5 kW in average. DC load in the school includes DC lighting and computers. A local DC bus at 24V is built to connect the DC load together. The DC load profile is assumed to be proportional to AC load profile. In the demonstration, the DC profile is only for illustration purpose. The realistic DC load profile in this school has not been measured. The DC peak demand accounts for average 12% of school term peak demand and 4% of holiday peak demand. A 10 kWp PV is installed at a school as DC renewable energy resources. The average output for each season shown in figure 4-12. The parameters of installed lithium-ion battery and converters are presented in table 4-3.

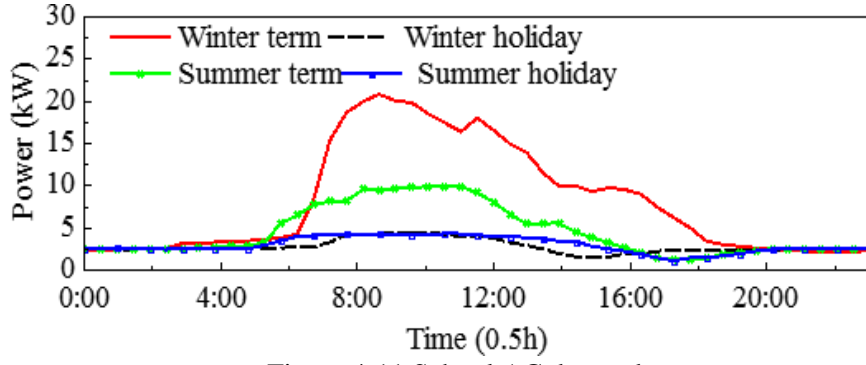


Figure 4-11 School AC demand

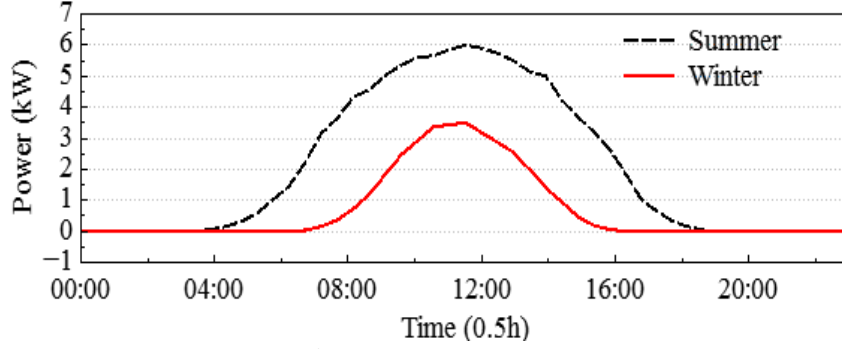


Figure 4-12 PV output

Table 4-3 Battery and converter parameters

Battery parameters	Unit	Converter parameters	Unit
Capacity	19.2kWh	Capacity	10.5kW
Max/Min SOC	0.9/0.3	Efficiency 1	0.91
Charging/Discharging current limit	180A	Efficiency 2	0.86

4.5.2 Optimal Results

A. Results of proposed formulation

Only the example-result of optimal battery operation in winter term weekday is shown in figure 4-13. The DC and AC power flow and demand change are illustrated in figure 4-14. In the winter time, there is maximal demand and minimal PV output. The numbers in parentheses indicate different battery behaviour steps, induced by TOU tariffs, PV output, AC and DC load. In detail: (1) Battery slightly discharges in the low price time to support DC demand and charges from the main grid to 90% of SOC. The DC load is supported by main grid during battery charging time. (2) Battery discharges to 30% of SOC to support both DC and AC load in the morning. The PV output during the daytime supports DC load and charges the battery when AC to DC power is zero. It supports the AC load when AC to DC power is negative. (3) Battery

charges from the main grid to 90% of SOC to take advantage of low prices. DC load is supported by both PV and main grid. (4) Battery discharges to 34% of SOC at the maximum rate, 4.3kW, supporting both DC and AC demand during the peak price time. (5) Surplus battery stored energy supplies the DC load during night shoulder price time. When low price comes, the battery slightly charges from the main grid to support DC load late night.

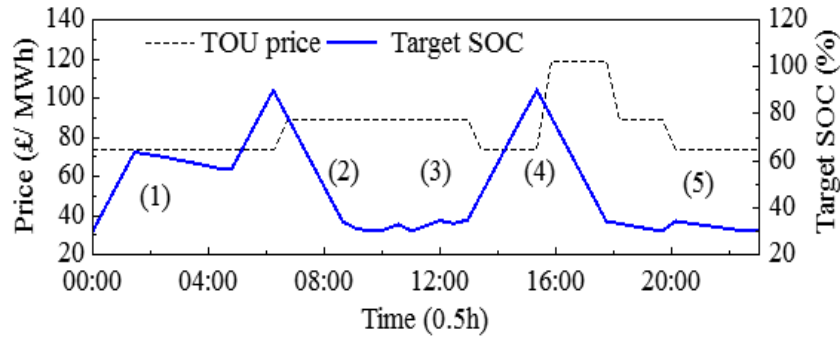


Figure 4-13 Winter term weekday SOC

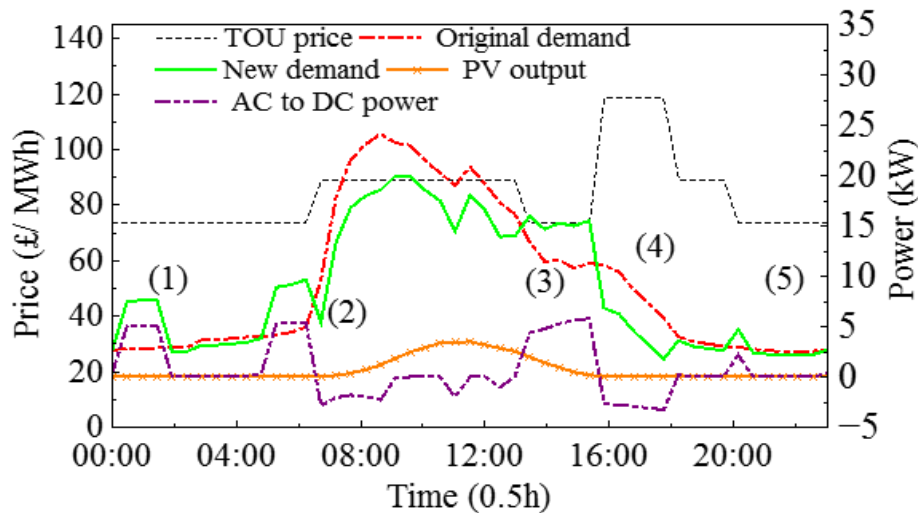


Figure 4-14 Winter term weekday demand

The school is located in the LV network with the demand profile shown in the figure 4-15. The figure gives an example of the network demand change in winter term time. The school located network's peak demand is at evening time, 18:30, and in winter term time the peak demand is 125.8kW. The DSR scheme in the winter term time achieves peak demand reduction by 3.25kW (2.5%).

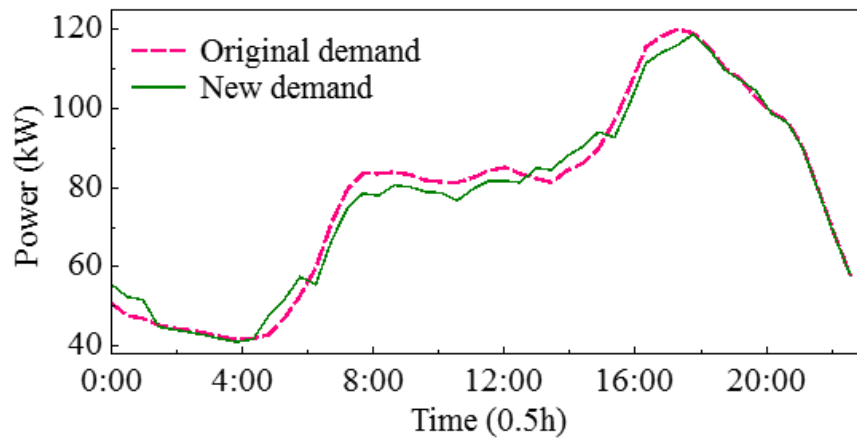


Figure 4-15 Network demand

Table 4-4 provides the results of energy cost saving, including both demand reduction and demand shifting savings and peak demand reduction.

The majority of cost saving differences between seasons comes from PV output. The energy management system brings average 10-20% energy cost saving in the winter and 42-67% in the summer. The cost saving differences between season mainly focus on demand reduction. The benefit of demand shifting brought by battery and TOU tariff is relatively constant, between 3.5-5%. Additionally, in the winter, the DSR scheme achieves higher peak demand reduction for the network, which is average 2%. The peak demand reduction effect in the winter is more evident since in the winter, the price peak and demand peak is more coincident.

With the demand and tariff variation, the cost savings and peak demand reductions vary with different day types. The number in bracket shows the amount of daily saving. The high demand in term time brings extra £0.5-0.7/day demand shifting saving than that in holiday weekday. The TOU price difference leads to £0.2/day saving increase in holiday weekend compared to holiday weekday. Both in the winter and summer, the peak demand reduction in the weekend is the relative higher, with 2.25% and 2.20% respectively, since there are longer evening high price time and with low DC demand, the main role of the DC bus is to achieve AC load shifting.

Table 4-4 Benefit quantification

Day type		Daily cost saving (%)		Peak demand reduction (%)
		Reduction(%)	Shifting(%)	
Winter	Term weekday	10.11 (£4.11)		2.5
		6.63	3.48 (£1.42)	
	Holiday weekday	18.94 (£3.41)		1.05
		14.94	4.00 (£0.72)	
	Holiday weekend	20.34 (£3.65)		2.25
		15.35	4.99 (£0.89)	
Summer	Term weekday	42.17 (£9.46)		0.2
		37.53	4.64 (£1.04)	
	Holiday weekday	68.11 (£8.89)		0.3
		64.50	3.61 (£0.47)	
	Holiday weekend	66.73 (£8.57)		2.20
		62.00	4.73 (£0.61)	

B. Comparison with single efficiency system

The battery SOC and AC-to-DC power are compared between traditional single efficiency model and proposed model. The single efficiency is 90%, which is equal to:

$$\eta_c = 0.03\eta_{5\%} + 0.06\eta_{10\%} + 0.13\eta_{20\%} + 0.1\eta_{30\%} + 0.48\eta_{50\%} + 0.2\eta_{100\%} \quad (4-32)$$

Where the index value is equal to the percent of converter capacity[107].

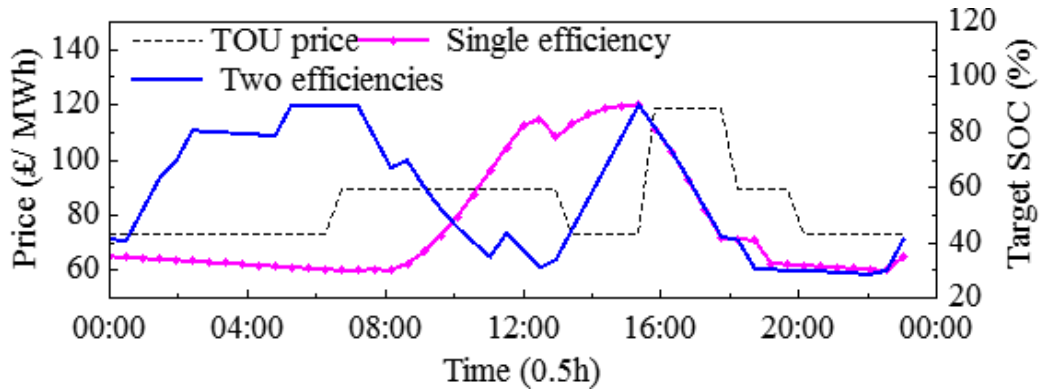


Figure 4-16 Winter holiday weekday SOC

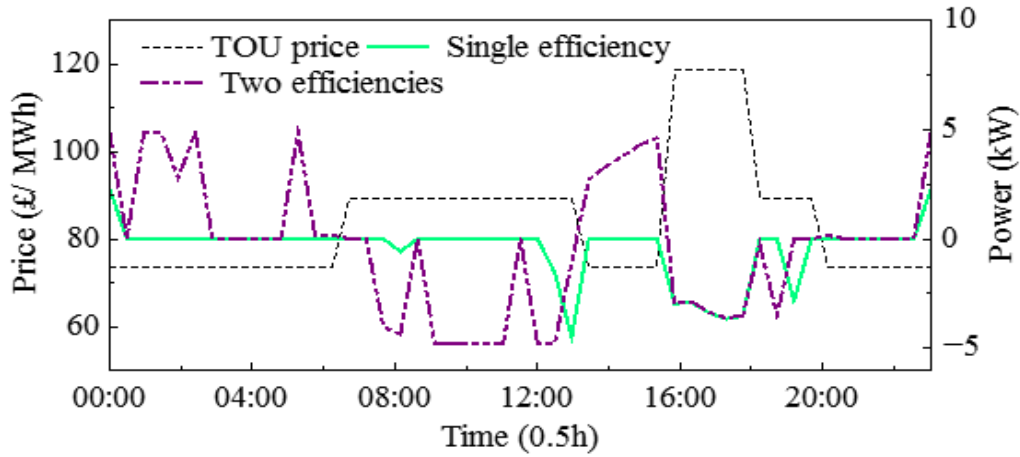


Figure 4-17 Winter holiday weekday AC-to-DC power

Table 4-5 Benefit comparison in demand shifting

Day type		Daily demand shifting cost saving increase (%)
Winter	Term weekday	2
	Holiday weekday	16
	Holiday weekend	3
Summer	Term weekday	8
	Holiday weekday	24
	Holiday weekend	16

The examples in winter holiday weekday are shown in figure 4-16 and figure 4-17. In the proposed two-efficiency model, the battery charges and discharges 60% of its SOC twice in the day to take advantage of low price overnight and in the afternoon. Consequently, DC bus supports AC demand shifting in both shoulder and peak price time. During the daytime, both PV and battery support the AC and DC demand in the school. However, in single efficiency model, major battery stored energy comes from PV output. There are limited AC demand shifting between low price time in the afternoon and peak price time, which limit the benefit.

As shown in table 4-5, the benefit of demand shifting in two-efficiency model in winter holiday weekday increase 16%, compared to single efficiency model. Additionally, in the single efficiency model, the DC-to-AC power in peak price time is always larger than the actual AC demand of school because of inaccuracy. The school pays for the extra power (the power loss), i.e. the school always pays for the electricity it does not use, which also limits the benefit receiving. The case is obvious in summer when original demand is low. The maximal benefit increase is in summer holiday weekday, which is 24%.

C. Comparison with traditional formulation

The optimization process and results are compared between the proposed piecewise function formulation and traditional formulation as shown in table 4-6. Both formulations are built in Java and resolved by an open source MIP C++ solver, CORIN-OR CBC [108]. Both formulations use single constant efficiency model. It is assumed the data collection time is different for each case, which introduces different time slot numbers for the whole day. In the optimization model, the battery input/output current limit is input as per unit time instead of per hour. Therefore, in different cases, the battery input/output energy limit per unit time is set differently. However, the final current limit per hour is slightly different in these cases and thus the objective values for different cases are located at different ranges.

It can be concluded that with the same optimization solver, the performance of the proposed formulation is better. The objective value of proposed formulation reduces 3%-5% compared with traditional formulation. The results also prove that with more data available, the proposed formulation significantly reduces the iteration number since it largely reduces the solution space. The iteration of proposed formulation is 5.8%-6.2% of the traditional model. When time slot is 48 and 96, the memory space of proposed formulation is 50% and 30% smaller. In the latter cases, memory space of proposed formulation is 6% and 12% larger than that of traditional formulation. The reason might be that the memory of objective and data management in the proposed formulation has higher proportions. When the number of input variables increases, more memory is created by java to manage the temporary data.

Table 4-6 Formulation comparison

Time slot number	Formulation	Objective value	Iteration	Memory space
48	Piecewise function	32.8	74	19MB
	Traditional formulation	33.7	56	38MB
96	Piecewise function	30.1	7	135MB
	Traditional formulation	31.0	115	194MB
192	Piecewise function	21.5	15	654MB
	Traditional formulation	22.5	244	615MB
240	Piecewise function	21.25	18	974MB
	Traditional formulation	22.4	314	869MB

4.6 Conclusion

This chapter has presented a new problem formulation of the DSR scheme in local hybrid AC/DC system and explored its efficacy in a school DSR performance. In the proposed model, the relationship between AC and DC power are transferred to the AC power drawn from the main grid by piecewise linear functions. This will substantially reduce the number of variables/constraints. Also, compared to traditional model considering constant conversion efficiency between AC and DC system, the model introduces power related conversion efficiencies and increase efficiency modelling capability. The demonstration illustrates that the proposed optimal formulation could bring up to 68% cost saving. It is also found that cost saving from demand shifting is relative constant through the year, between 3.5-5%. However, the total cost saving in summer is higher than that in winter because of high PV output; in the holiday is higher than that in term time because of low demand; in weekend is higher than that in weekday because of the tariff. Additionally, the results show that efficiency is an import factor in the performance of DSR: the efficiency determines whether the AC demand shifting in DSR using local DC network is effective and economical. Compared to traditional one efficiency model, the proposed model with power related efficiency could increase the cost saving up to 24%. Additionally, the proposed model provides

better optimization results as the objective value of proposed problem reduces 3%-5% compared to traditional formulation.

Chapter 5. Multi-functional EMS for Maximum Benefit of Network

Chapter 4 has proposed a DSR strategy for maximum customer energy bill saving. However, the aim and core value of the DSR are to transfer the individual customer's benefit to wider system benefit and thus reduce the whole system planning and operation cost. Therefore, a multi-functional EMS responding to both network pressure and energy cost is proposed in this chapter. The EMS primarily fulfil the network peak demand reduction request for maximum network (whole system) benefit and then maximize the customers' electricity bill saving based on TOU tariff. The work is based a practical trial in smart grid project "Sola Bristol". Both the simulation results and practical trail results are discussed. The analysis provides an analysis on the difference between the realistic DSR performances on network demand reduction and the results in the simulation.

5.1 Introduction

The distribution network would face increasing load pressure as the introduction of LCTs. It is estimated that electrification of transport and heating could add an additional 5-15% electricity demand by 2030 [109]. The dramatically increased demand is expected to make low voltage network more vulnerable. However, considering the flexible characteristic of these loads, DSR, including the smart control of LCTs, is an effective and economical solution to solve these challenges. This is because conventional network reinforcement for short thermal overloads may not the most efficient use of customers' money.

Specifically, for system planning and operation, DSR is essential to reduce peak demand, thereby alleviating the requirement from emergent generation, mitigating the network congestions and reducing network investment. There has been significant amount of researches focused on designing DSR operation algorithms to bring benefit for network operator. The DSR strategies are design to either shift household appliance [110-113] or control LCTs [114-118] for customers in order to shave peak, flatten demand curve or defer network investment. The typical researches are as follows. The authors in [111] propose a scheduling scheme aim to achieve constant demand during the day. The study classifies the home appliances into "soft load" and "hard load", which are shiftable and non-shiftable. The scheduling scheme is to shift the "soft loads" to the time with trough "hard load", like to fill the water into a ponding and finally

achieve “water level” alike constant demand. The authors in [112] propose a network congestion game where each user allocates demand as a response of other user actions. The aim is to converge to a stable equilibrium point with smooth electricity demand on the distribution network. The authors in [113] develop the system based DSR control that residential optimal DSR is modelled as an optimal power flow (OPF) problem on the network. In the proposed method, the original demand is set as input of OPF. Then, based on the OPF results, the connected customers are required to inject or reduce power in certain time and locations. The authors in [117] propose a new price scheme and design an optimization model adopting alternation direction method of multiplier for maximum DSR benefit. The aim of the optimization is to minimize the electricity bill of the whole network thus to flatten the demand curve on the network. The study in [118] proposes an alternative individual billing mechanism DSR model. In the model, each customer submits a defined number of candidate load profiles with the rank of preference that corresponds to the next day’s needs. A centralized DSR aggregator then select an optimal combination of the individual daily load profiles to minimize cost and flatten the network demand.

Majority of the previous DSR model designed for mitigate network pressure is either through minimum customer electricity cost or minimum peak-to- average ratio. In the studies to minimum electricity cost, including the previous chapters, network peak demand reduction is achieved by synchronized high price and network peak demand. The network peak demand reduction is actually an important by-product of minimum electricity cost. However, in LV network, where the demand is quite diverse and uncertain, the peak demand might not coincident with the accumulated customers’ peak demand derived from typical load profiles (or sampled customer load profiles). It is always the case that extreme weather and public holidays in winter create demand peak on LV network [119].

With the development of smart metering, communication and remote control system, the DNOs and customers could share the ownership of the energy storage to increase the benefit to both customers and network operators. Two predefined shared battery operation strategies have been proposed. The previous study [114] proposed the fixed and dynamic battery capacity share strategies between DNOs and customers. The method determined the ownership of the battery capacity in different days of the year

between DNOs and customers. However, the formulation is unable to vary the battery capacity ownership during the day with the variation of energy price and network condition. The following studies [48, 120] proposed a battery capacity reservation strategy to ensure the available battery capacity for network usage during different time of the day. The battery operation strategy was to follow the pattern of designed “Charging envelope”, which was used to mitigate the network pressure. The “Charging envelope” was designed based on network situation and thus all the customers on the network would follow the similar battery operation pattern. Since the differences between customer load profiles would largely impact the DSR strategy and benefit [121]. With similar battery operation pattern, certain customers cannot experience the maximum benefit and would even have no benefit at all.

Therefore, the original EMS is extended to a new multi-functional EMS to maximize the customer benefits and respond to network request during certain peak time, which might or might not coincident with the TOU peak price time. This new EMS extends the previous customer based EMS by adding network request into optimization formulation. In this new optimization model, the network request will be primarily fulfilled for whole system benefits. This is because the short time use of DSR during critical peak demand time would bring significant benefit on network investment deferral, by which, it could save large amount of customers’ money in reinforcement new network infrastructure. The new EMS could be taken as a complement of previous “shared battery” studies to support the smart grid trial project, “Sola Bristol”, in the UK. Especially, the proposed formulation is used to simulate the final DSR strategy in the project.

Additionally, the study for the first time provides an insight on how the realistic DSR performance on network demand reduction and how the results are different from what are expected in the simulation. The results of simulated and implemented DSR strategy in the practical system are discussed in this chapter.

The rest of chapter is organized as follows: Section 5.2 introduces the DSR strategies designed and implemented in the smart grid project; Section 5.3 proposes the optimization model; Section 5.4 introduce the network benefit quantification method; Section 5.5 provides the trial network information; Section 5.6 demonstrates the simulated network demand reduction performance; Section 5.7 provides the real DSR

performance on network and discuss the differences with estimated results and the reasons for the differences; and Section 5.8 draws the conclusion.

5.2 DSR strategy in Sola Bristol Project

Sola Bristol project is an alternative solution that seeks to accommodate high-density PV generation economically through using energy storage and smart tariffs. The project objectives are 1) to solve network problems when a large number of PV integration into LV networks; 2) investigate how in-home battery provides benefits to customers and aid the DNO with network management, including peak demand reduction [59]. SoLa Bristol has engaged 26 domestic customers, 5 schools and an office to participate in the project, with solar PV and a battery installed. In the participants' properties, the battery storage is featured with shared ownership between customers and DNOs. The DNO is able to communicate with the battery to charge and discharge it to help with network management.

There are two DSR strategies achieved by the EMS and battery storage.

- Price driven DSR strategy

Without DNO requirement, the EMS control system is operated based on PV output, demand and TOU tariff [122]. The used TOU tariff is designed based on the wholesale energy price [106]. The control system is designed with the efficacies: 1) during the daytime with high PV output and shoulder price, the battery is charged by PV; 2) during evening time with demand and price peak, battery discharges to save electricity bill and reduce peak demand.

- DNO driven DSR strategy

Otherwise, the battery is operated by network operators remotely in response to network undesired conditions, such as network congestion and voltage violation caused by PV, or help to reduce network peak demand directly. The battery storage will be discharged assigned energy or its fully available energy when received the request of the network operator. However, apart from the short time period that DNO controls the battery, EMS will be operated under price driven DSR strategy for maximum customer

benefits.

5.3 Multi-functional EMS model

5.3.1 Overview of Multi-functional EMS

The structure of the multi-functional EMS is similar with the previous EMS system with the exception of network request. In detail, the charge controller is specified as battery charge controller.

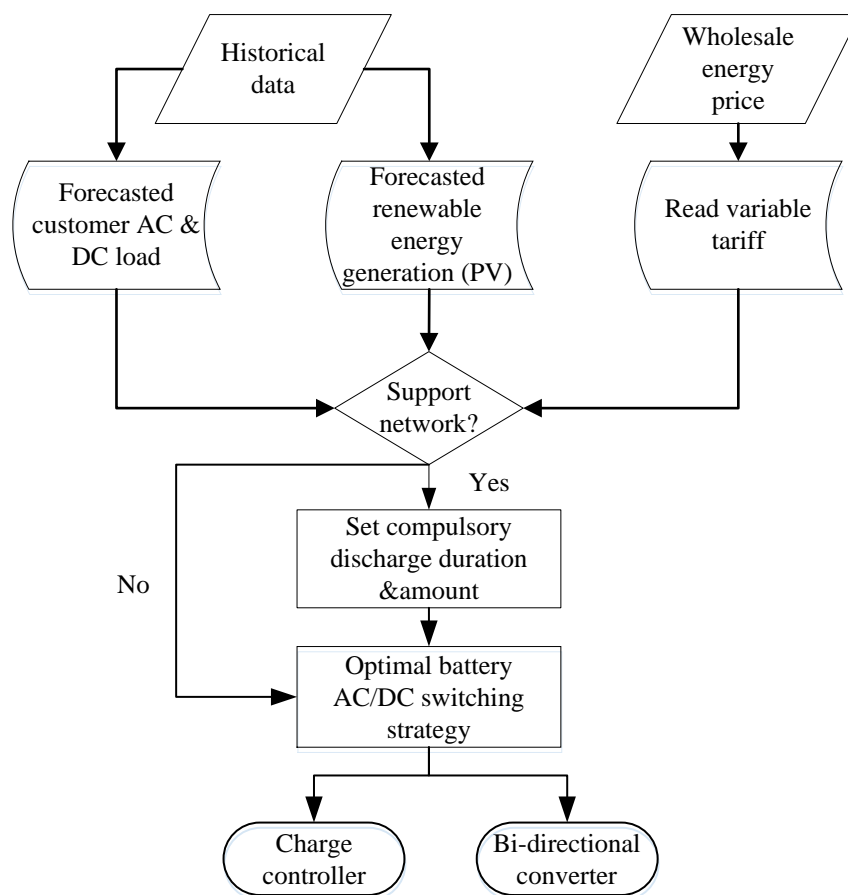


Figure 5-1 Overview of multi-functional EMS

5.3.2 Simulated optimization model

The multi-functional EMS optimization model is largely based on the model proposed in chapter 4. However, the network request is added in the optimization to ensure DSR would primarily benefit system at the peak demand time. The detailed mathematical formulation is presented in this section. The network request is

represented as the equations 5-10.

$$\text{Min} \sum_{t=1}^{48} C(t)P(t)T \quad (5-1)$$

$$C(t)P_{AC}(t)^* = \begin{cases} U(t)P_{AC}(t) & \text{if } P_{AC}(t) \geq 0 \\ S(t)P_{AC}(t) & \text{if } P_{AC}(t) < 0 \end{cases} \quad (5-2)$$

$$\text{s.t. } P(t) = P_{load}(t) + P_S(t) - P_{PV}(t) \quad (5-3)$$

$$P_D^{max} \leq P_S(t) \leq P_C^{max} \quad (5-4)$$

$$E_{min} \leq E(t) \leq E_{max} \quad (5-5)$$

$$E_{min} = SOC_{min} \times B \quad (5-6)$$

$$E_{max} = SOC_{max} \times B \quad (5-7)$$

$$\begin{cases} E(t) = E(t-1) + \Delta E(t) & t = 1, 2, \dots, 48 \\ \Delta E(t) = P_S(t)T \end{cases} \quad (5-8)$$

$$\sum_{t=1}^{48} P_S(t) = 0 \quad (5-9)$$

$$P_D^{max} \leq P_S(t^*) \leq P_r \quad (5-10)$$

When there is network request, the battery needs to discharge to mitigate network pressure with certain time t^* . The network operator would send a specific minimum discharge rate, P_r , where $P_r < 0$. The battery discharges between P_r to maximum discharge rate.

The optimization model is formulated as the piecewise functions proposed in previous chapters. The constraints on network request are transferred to battery power constraints and are built in piecewise function though the value range $[P_{DC}^{min}, P_{DC}^{max}]$ as shown in the figure 5-2. The piecewise function is converted into mixed integer model and be solved by MILP.

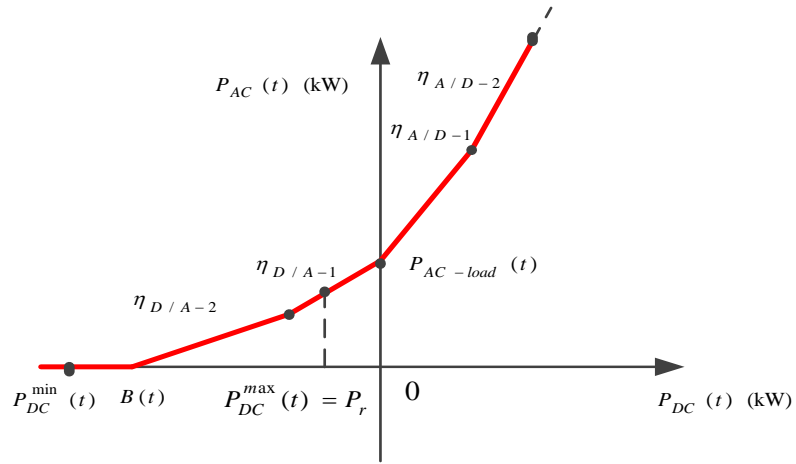


Figure 5-2 The piecewise function representation with network request

The overview of the optimization process is shown in figure 5-3. The network request is added to the optimization process as a constraint. The constraint is input into the settings of value range of the piecewise functions.

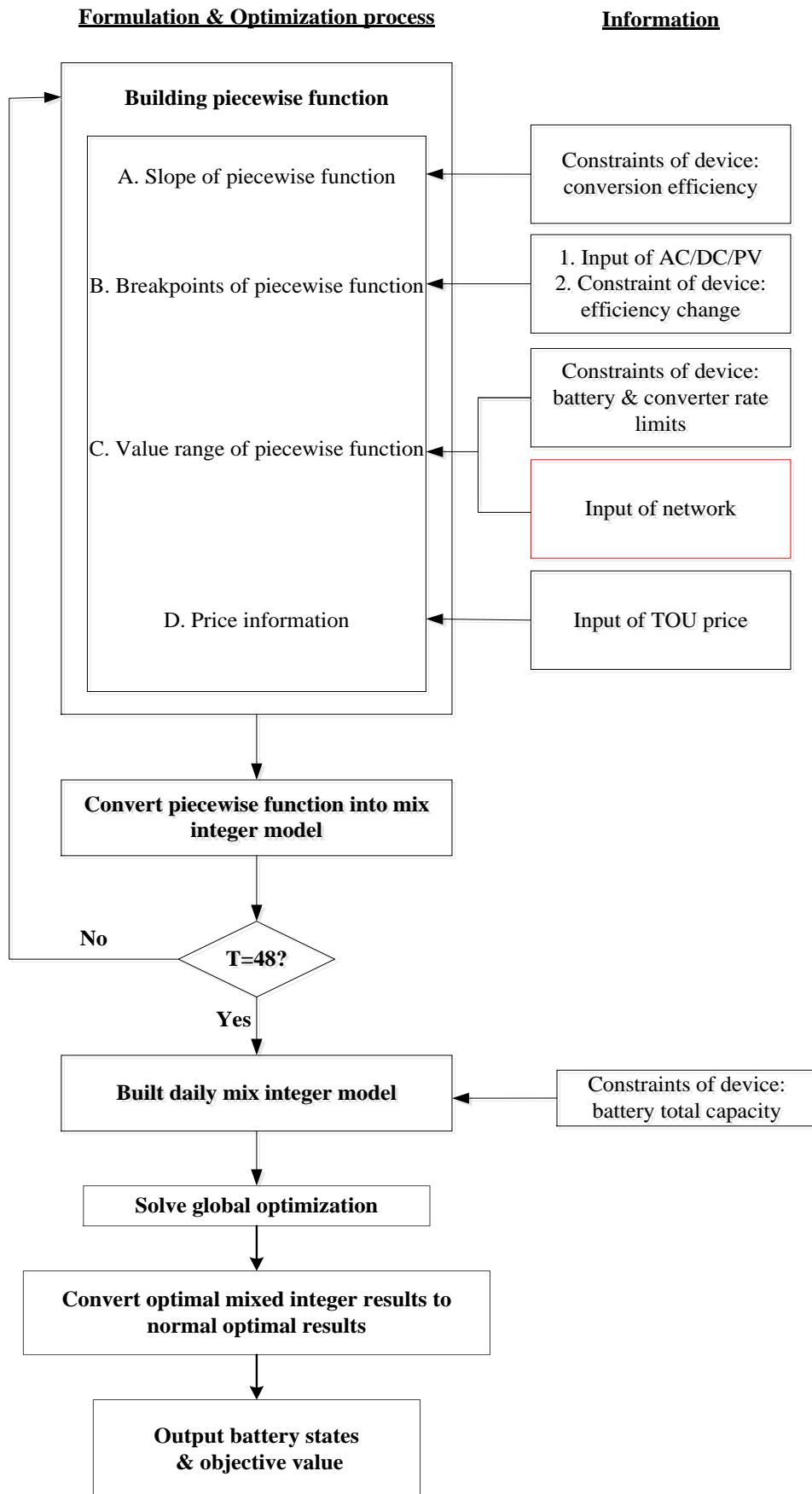


Figure 5-3 Flowchart of optimization problem solving with network request

5.4 Benefits quantification method of investment deferral

The benefit in network investment deferral is quantified by evaluating the changes in the present value of the future investment before and after integrating energy management system. The mathematical formulation is shown as follows, which is based on Long-run Incremental Cost (LRIC) charging method [123]:

$$\Delta PV = PV - PV_{new} \quad (5-11)$$

Where PV and PV_{new} are present values of the future investment before and after integrating energy management system.

The present values can be calculated as:

$$PV = \frac{Asset}{(1+d)^n} \quad (5-12)$$

$$PV_{new} = \frac{Asset}{(1+d)^{n_{new}}} \quad (5-13)$$

Where: $Asset$ is the modern equivalent assets cost; d is discount rate; n and n_{new} are the years to invest a network asset before and after integrating energy management system.

It is assumed that the investment will occur when the feeder/transformer is fully loaded. With this assumption, the year to invest a network asset is determined by the load peak. The network component (asset) capacity and load growth rate as shown below:

$$n = \frac{\log RC - \log D}{\log(1+r)} \quad (5-14)$$

$$n_{new} = \frac{\log RC - \log D_{new}}{\log(1+r)} \quad (5-15)$$

Where: RC is the network component (asset) capacity, D and D_{new} are the network peak load before and after integrating energy management system, r is the load growth rate.

5.5 Test system in trial network

5.5.1 Network layout and peak demand

The test network's layout is shown in figure 5-4. The total customer in the test network is 257 with 136 in feeder 0011 and 121 in feeder 0021. There are 3 and 8 domestic houses take part in the project at feeder 0011 and 0021 respectively. The houses' connection points are listed in table 5-1.

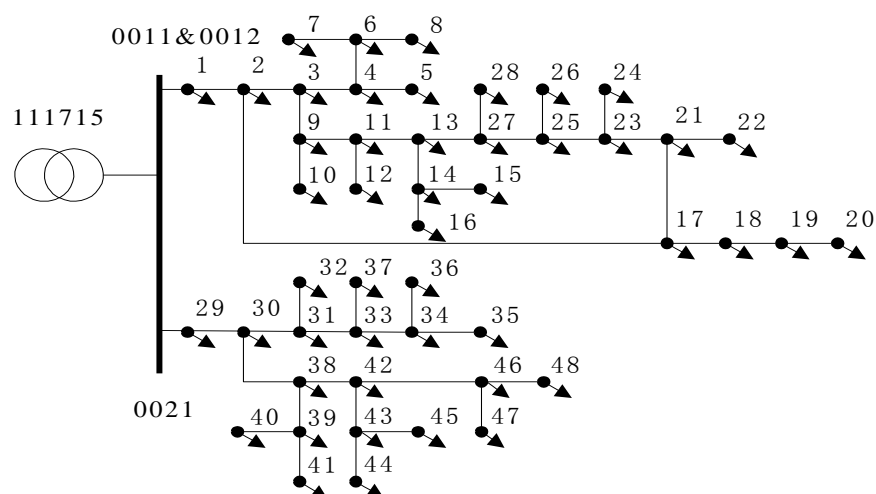


Figure 5-4 Tested network layout

Table 5-1 Household connection points

<i>Feeder No.</i>	<i>Total Customer No.</i>	<i>House No.</i>	<i>Connection point</i>
0011	136	1	Node 3
		2	Node 6
		3	Node 6
0021	121	4	Node 46
		5	Node 46
		6	Node 38
		7	Node 38
		8	Node 39
		9	Node 30
		10	Node 33
		11	Node 31

The measured peak demand of the two feeders and the substation in the test network in 2014-2015 year is shown in the table 5-2. The load profiles of the peak demand days are shown in figure 5-5 to figure 5-7 for Feeder 1, Feeder2 and substation respectively.

The results show that on the test LV network, the demand peak of Feeder1 and transformer are at noon time during Christmas holiday, which are not coincident with the cumulative customer typical load profiles. The demand peak of Feeder 2 is located at evening time in winter as typical domestic load profiles. The demand peak happens under the situation of extremely cold weather.

As the references, the demand profiles of Feeder 1, Feeder 2 and Substation on four days, 25/12/2014, 28/12/2014, 05/02/2015 and 08/02/2015 are shown in the figures 5-8 to 5-10. The figures show that during the Christmas holiday, the demand during daytime is high. However, in February, the load profiles of the feeders and substation are similar with the typical load profiles of the domestic customer.

The result proves that in the LV networks, the network peak demand might locate in special holidays and during the daytime, which is determined by the customers' living behaviours. Along with the load growth, the network load profiles will keep the similar pattern with the stable living behaviours.

Table 5-2 Measured network peak demand

	<i>Power (kW)</i>	<i>Date</i>	<i>Time</i>
Feeder 1	164.1	28/12/2014	12:45
Feeder 2	171.5	5/2/2015	17:30
Transformer	317.7	25/12/2014	11:45

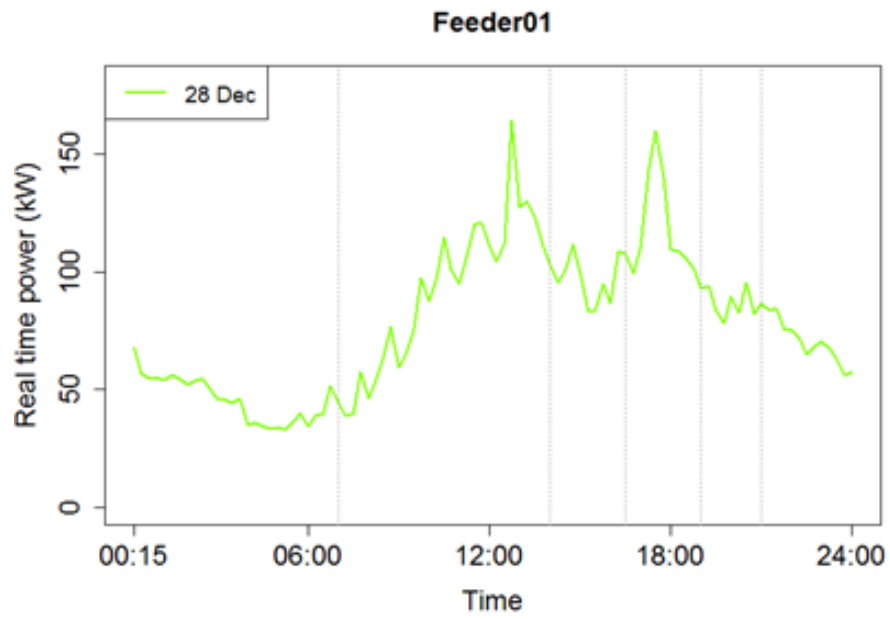


Figure 5-5 Peak demand of Feeder 1

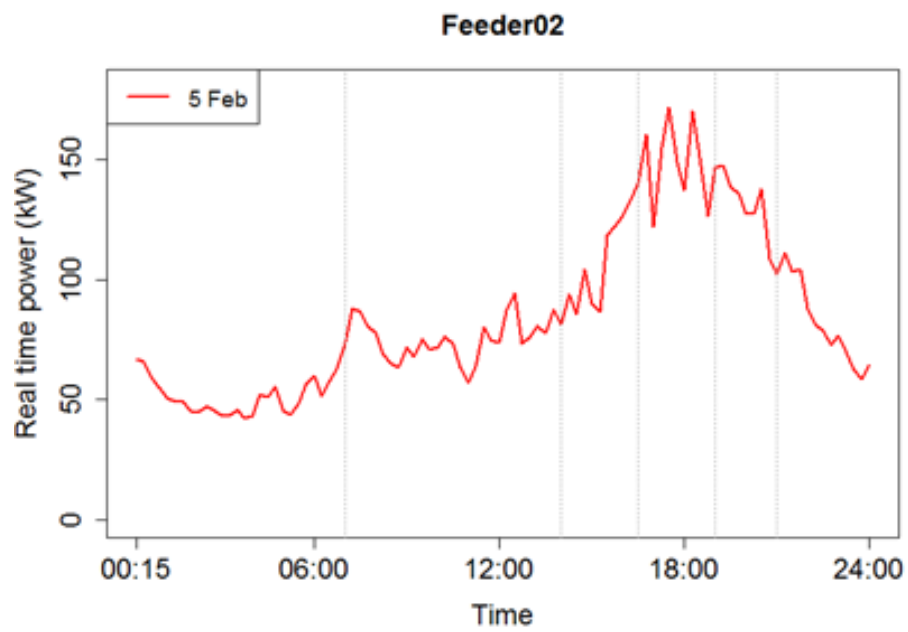


Figure 5-6 Peak demand of Feeder 2

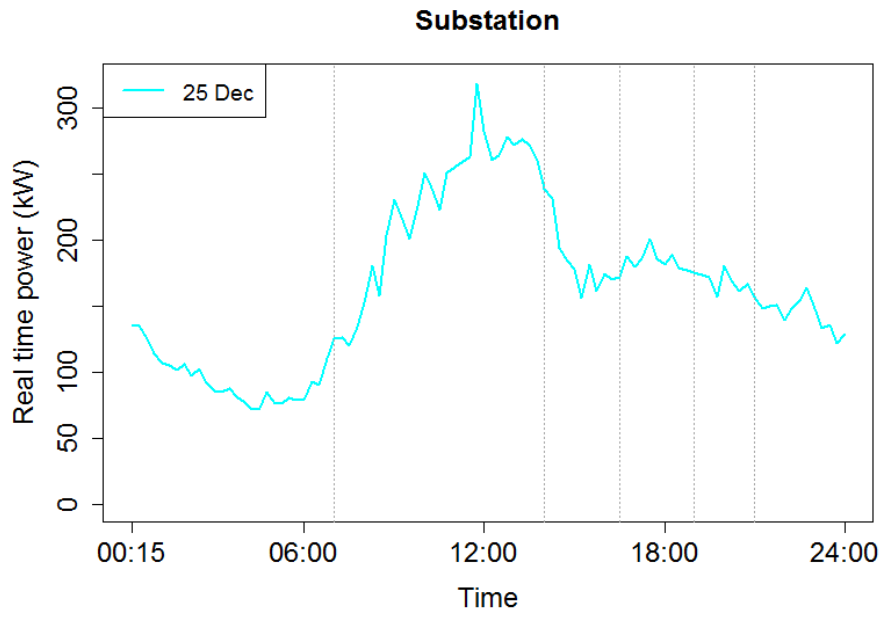


Figure 5-7 Peak demand of network

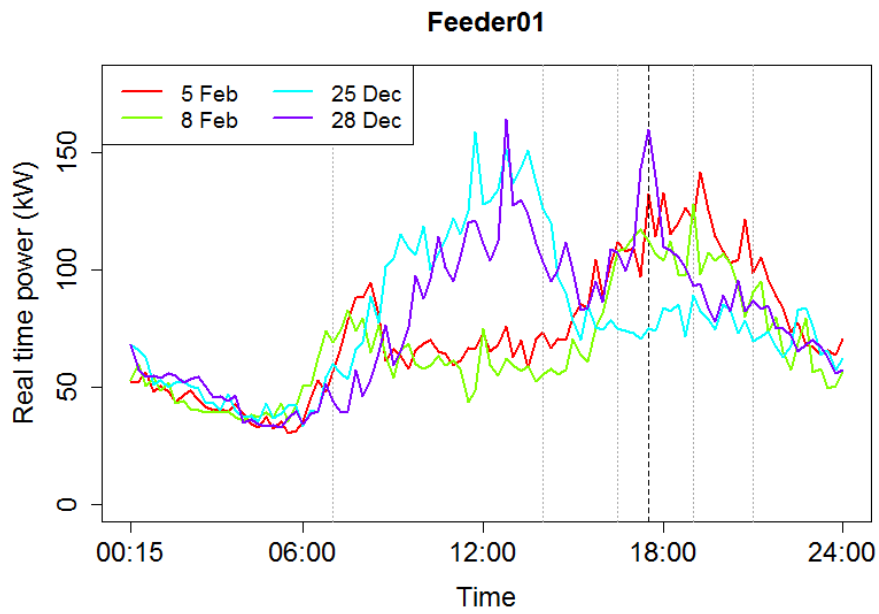


Figure 5-8 Load profiles of Feeder 1

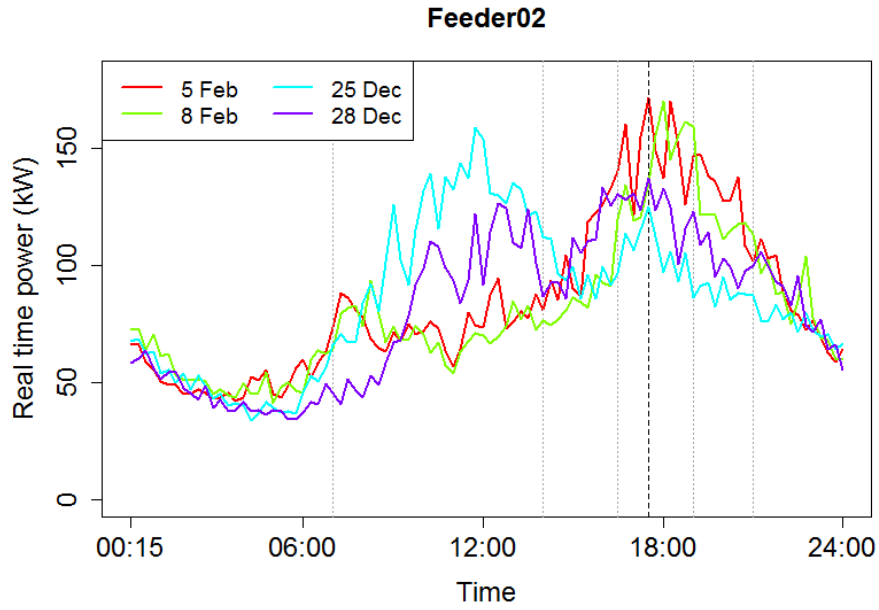


Figure 5-9 Load profiles of Feeder 2

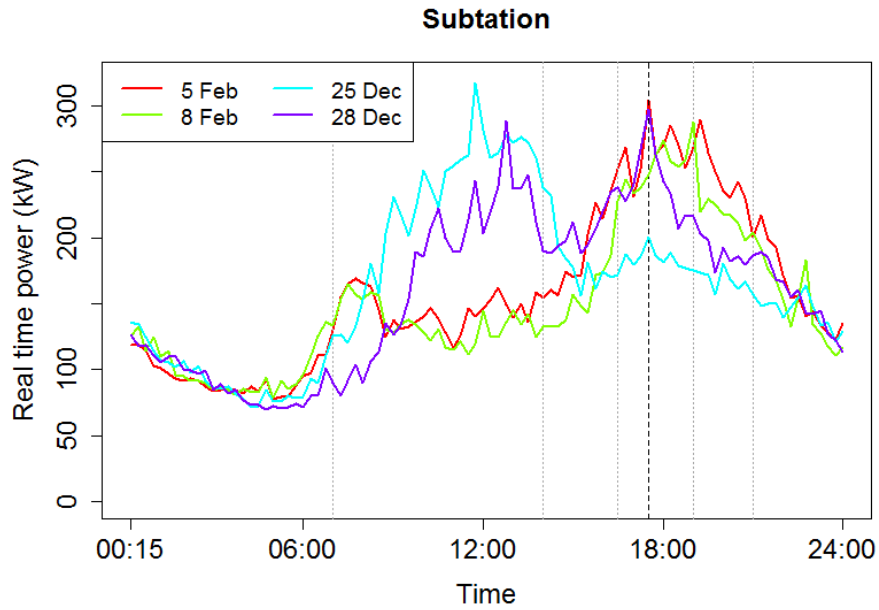


Figure 5-10 Load profiles of substation

5.5.2 Devices parameters

The parameters of battery storage and converter integrated into engaged households are shown in table 5-3. PV capacity of the households is 2.5kWp.

Table 5-3 Battery parameters

Battery parameters	Unit	Converter parameters	Unit
Capacity	4.8kWh	Capacity	3.2kW
Voltage	24V	Efficiency 1	0.91
Max/Min SOC	0.9/0.3	Efficiency 2	0.86
Charging/Discharging current limit	50A		

5.6 Estimate DSR performance in trial network

The customer's load profile and PV output is shown in figure 5-11. The typical domestic load profile of UK [46] is used to simulate the DSR performance in this study. The winter load and PV output is applied since the aim is to mitigate the network peak demand during the winter. The TOU price implemented in the project is shown in figure 5-12. The TOU price reflects the current wholesale energy price. The peak price time is coincident with the estimated peak demand time of early evening. The price will also encourage reduce demand during early evening time.

Based on the measured network demand data, the EMS will implement two scenarios: 1) network demand reduction between 11:00-13:00 and 2) between 16:00-18:00. The battery discharges to support network based on the equation (5-10) in the EMS model. The two scenarios could be seen as the different requirements for customers on two different feeders. The two scenarios also represent two highly possible cases when LV network reaches peak demand: Christmas holiday and cold weather. The network operator invests the network infrastructure based on that the peak demand reaches the capacity of the network. To reduce the peak demand in the two time intervals during Christmas holiday or cold weather date will help to defer the network investment.

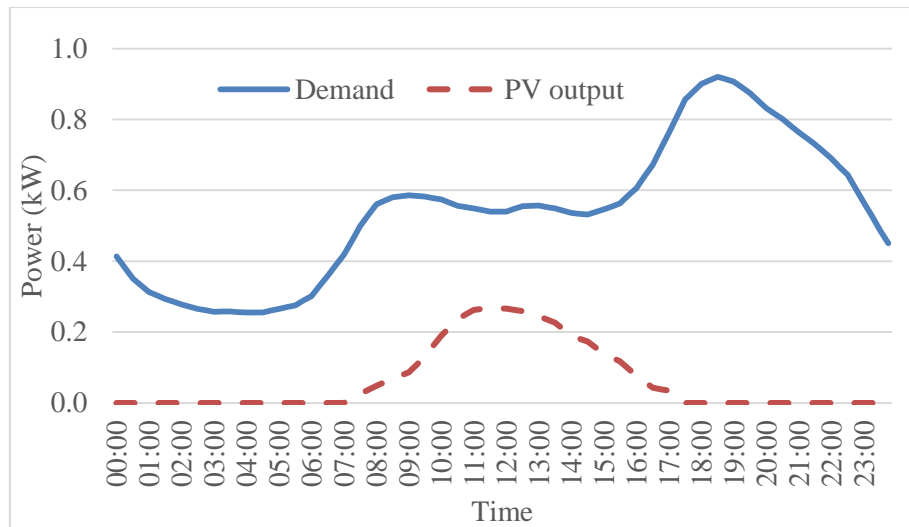


Figure 5-11 Typical load profile and PV output

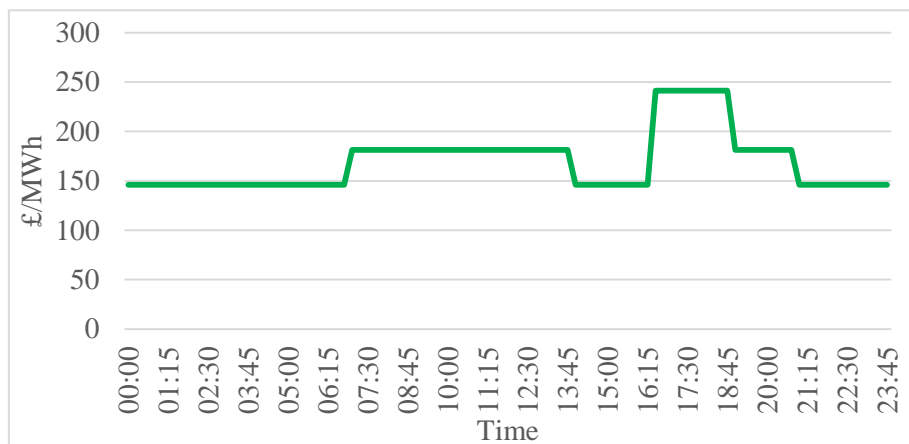


Figure 5-12 TOU tariff

The results of electricity bill saving are shown in table 5-4. The price driven DSR strategy could bring 17.7% electricity bill savings. To fulfil the network request on evening peak demand reduction, customers only sacrifice 5% of the bill savings. But to reduce the demand during noon time largely reduce the customers' saving to 3.75%.

Table 5-4 Customer bill savings with network request

Scenarios	Electricity bill saving	
	£0.41	17.73%
No network request		
Network request for Feeder 1 and transformer	£0.09	3.75%
Network request for Feeder 2	£0.29	12.55%

The battery DSR operation of customers in feeder 1 and transformer is shown in figure 5-13. To reduce the peak demand during noon time, the battery is forced to discharge with maximum rate during 11:00-13:00. Before fully discharge during the noon time, battery needs to charge back to maximum SOC even the energy is bought with shoulder price.

The results of the DSR operation on feeder 2 is shown in figure 5-14. The battery SOC is similar with that in price driven DSR strategy, except the discharging rate is constant high during the peak time. The SOC reaches its lower limit early at 18:30.

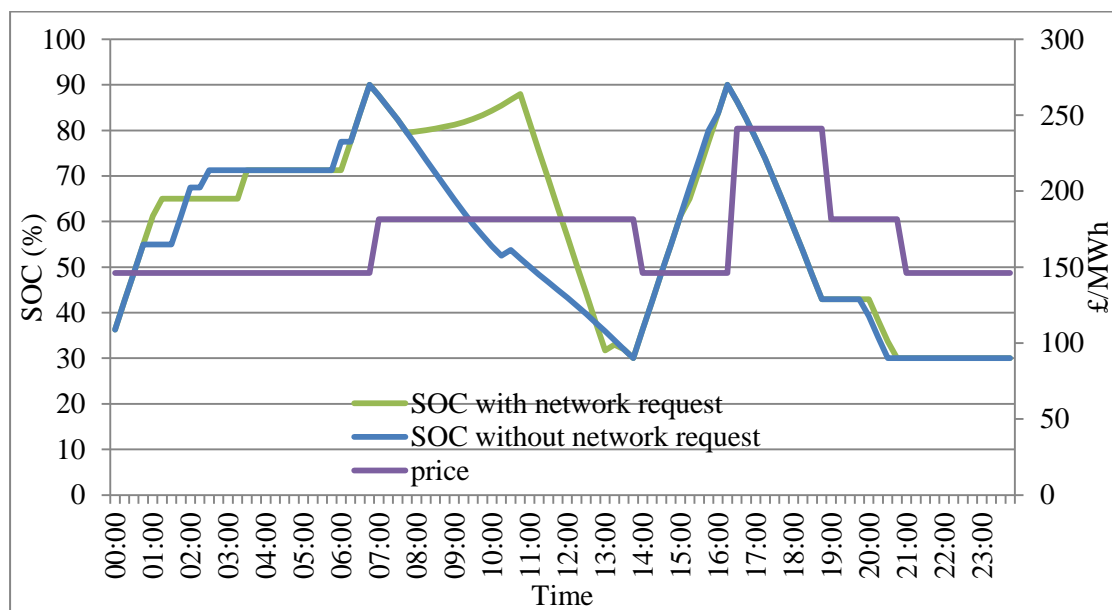


Figure 5-13 Battery SOC with noon time network request

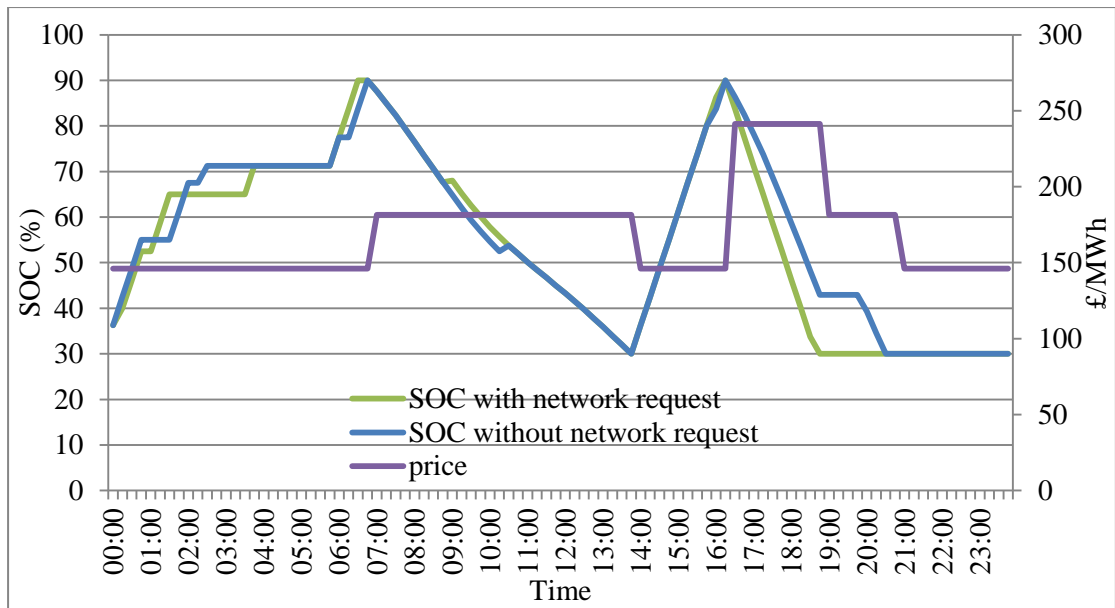


Figure 5-14 Battery SOC with evening time network request

The corresponding customer demand change is shown in figure 5-15 to figure 5-17. The demand change of price driven DSR is shown in figure 5-15 as the base case. The strategy takes full advantage of TOU price that shift twice in one day. The demand during shoulder price in the morning and peak price in early evening is shifted to off-peak price periods. The demand at 10:30 does not be shifted since the battery is charged by PV. The demand at 10:30 does not be shifted since the battery is charged by PV.

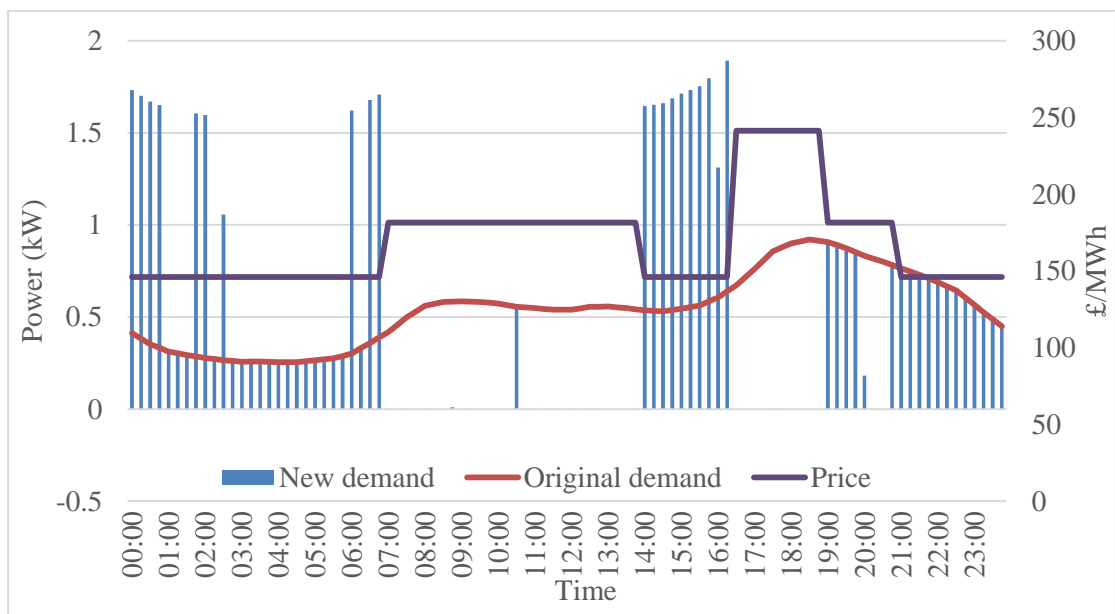


Figure 5-15 Customer demand change without network request

Customer will export average 0.7kW freely during noon time when receive the request from network operators as shown in figure 5-16. And the new demand does not exceed the original demand during daytime, which indicates the battery is charged from PV output before discharging at maximum rate to support network.

Compare with the case 1, the export power, averaging 0.3kW, is smaller than that in case 2 since the original customer demand is high during evening as shown in figure 5-17. Majority of the battery discharged power reduces customer's own demand, which will bring benefit to the customer.

Therefore, the benefit reduction of the customer is derived from free export behaviour. The larger the export power, the lower the benefit received.

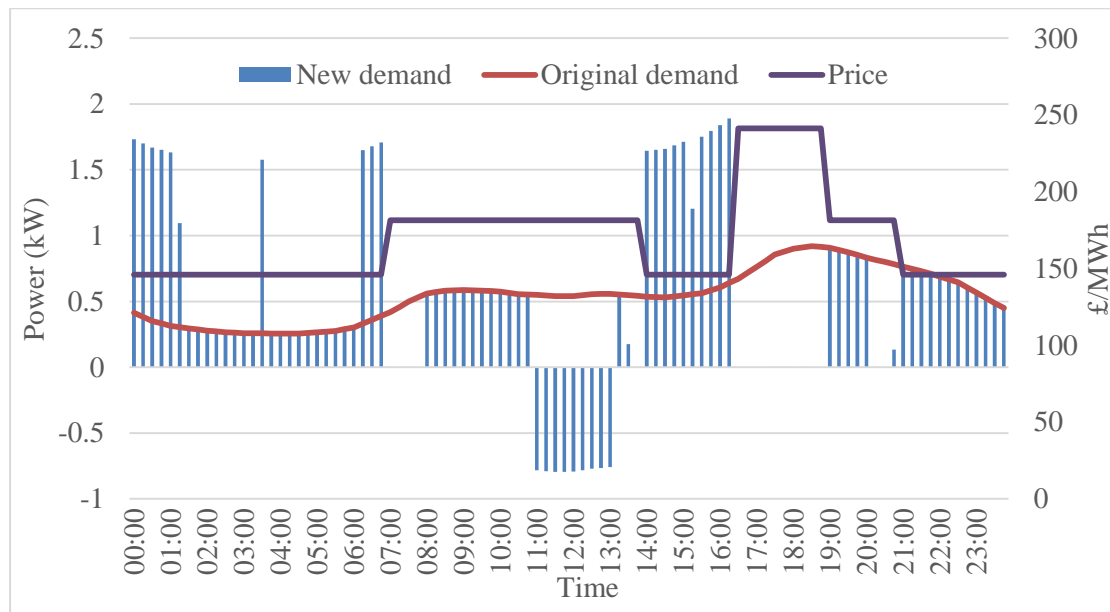


Figure 5-16 Customer demand change with noon time network request

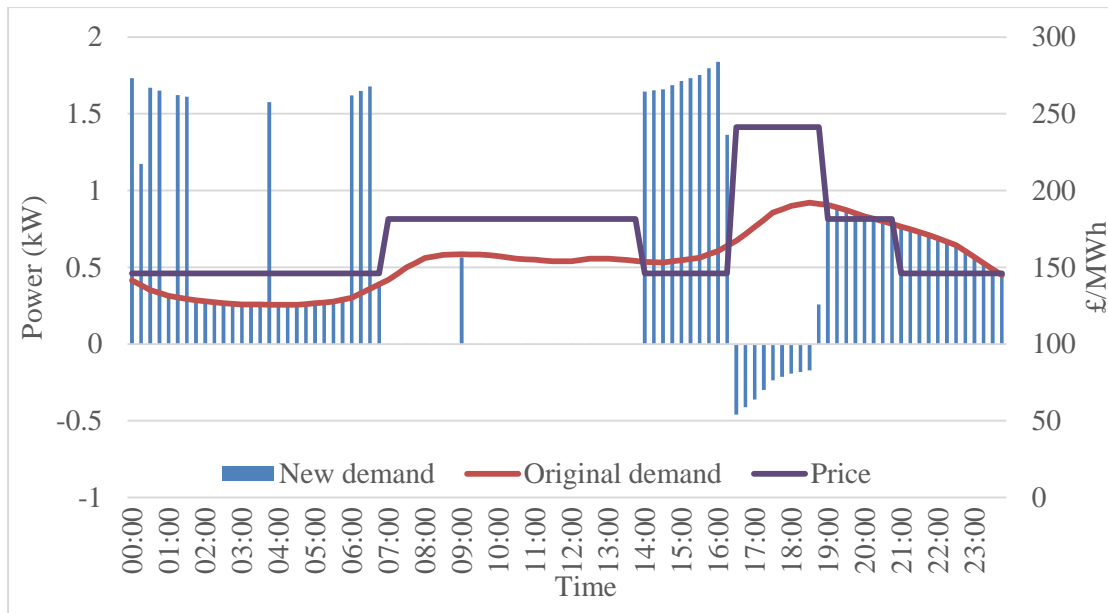


Figure 5-17 Customer Demand change with evening time network request

Given the reduced demand and export power, the network demand reduction benefit is calculated. It is assumed that the load growth is 2% and the discount rate is at 5.6% [124]. The typical unit cost of feeder was £67200/km and the unit cost of transformers was £26400 [125].

The result of investment deferral of the test substation is shown in table 5-5. The result is calculated by the method demonstrated in section 5.4. However, if all the customers on the feeder charge the battery during low price time as shown in the figures, a new network demand peak will be created. Therefore, only 12.5% penetration of EMS is considered. Given the capacity of the test substation is 750kVA, the network utilization of the test substation is found to be 42%. When the utilization is increased to 85%, the investment deferral is shown in table 5-6.

Table 5-5 Network investment deferral with 42% network utilization		
	<i>Current penetration (4.3%)</i>	<i>12.5% penetration</i>
Transformer	£362.2	£800
Feeder 1	£70.6	£903
Feeder 2	£701.2	£1335
Total	£1134	£3038

Table 5-6 Network investment deferral with 85% network utilization

	<i>Current penetration (4.3%)</i>	<i>12.5% penetration</i>
Transformer	£1247	£2864
Feeder 1	£242.5	£3224
Feeder 2	£2434.2	£4743.9
Total	£3923.7	£10831.9

5.7 Realistic DSR performance in trial network

5.7.1 DNO driven DSR strategy trial

A network request DSR trial was conducted on 20th, 22nd and 28th April 2015 to verify the network peak demand reduction effect. In the trial, the battery storage will be discharged 1-2 kW during settled network peak demand time when received the request of the network operator. While, the battery charge request is also applied into the trial to ensure the operation safety of the battery. In detail, the DSR strategy was shown in table 5-7.

Table 5-7 DNO-driven DSR strategy

<i>Time of Day</i>	<i>Network request</i>	<i>Aim</i>
00:00-14:29	No force charging/discharging	--
14:30-16:29	Force charge the battery	Ensure the battery has enough stored energy to support the network requirement
16:30-16:59	Remove the force charging from the battery	Price-driven strategy operated and battery slowly discharged to the target SOC of 90%
17:00-18:14	Force discharge of the battery	Various rates discharging between 1-2 kW at each 15 min interval
18:15-18:59	Force charge the battery	Reach the target SOC of 60%
19:00-23:59	No force charging/discharging	--

5.7.2 DSR performance on demand reduction

The performance of both price-driven DSR and DNO driven DSR is illustrated in

this section. The results are derived from the measured data of 3 price-driven DSR days and 3 DNO-driven DSR days. The performance of price-driven DSR and DNO-drive DSR in the typical household is shown in figure 5-18.

The network trial performance clearly shows that between 17:00-18:14 (“force discharge” stage), the average demands are negative in both DNO driven DSR days and price-driven DSR days. In both cases, the customer exports power to the grid. However, the export behaviours are driven by different reasons, one is the force to discharge requirement and the other is the high price. The results between 17:00-18:14 are similar with the simulation results when apply the evening demand reduction requirement shown in figure 5-17. The average exporting power during 17:00-18:14 on DNO-drive days and price-driven days are 0.3kW and 0.2kW respectively.

Between 14:30-16:00 and 18:15-18:59, DNO-drive DSR forces the battery charge from the main grid while price-driven DSR lets the battery charge from PV output and discharge to support demand respectively. It is suggested that the household’s demand on DNO driven DSR days is up to 1kW higher than that on price-driven DSR days in these two periods shown in green and orange arrows.

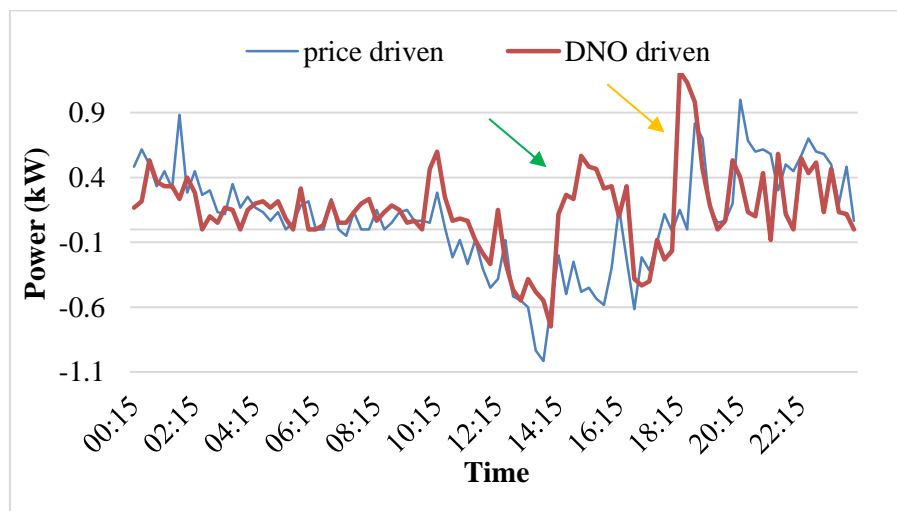


Figure 5-18 Household load profiles comparison

The performance of price-driven DSR and DNO-drive DSR on the network is shown in figure 5-19. The network effect is analysed based on the demand of phase 3 in feeder 0021 since the DSR penetration rate is highest in this phase: 10% of households connected at phase 3 have in-home batteries to achieve DSR (4 households in the total

40 households). The load profiles are impossible be identical between any two days. The random electricity usage in household, weather and any special event within the community could bring variability in network demand.

The total household demand increase brought by the force charging request is clearly shown in figure 5-19 between 14:30-16:29 and 18:15-18:59 pointed as green and orange arrows. There are up to 2kW and 3kW demand increase introduced by batteries of 4 tested households.

However, the demand increase cannot be identified on networks. On DNO-driven DSR days, there are two small demand peaks, also pointed as green and orange arrows, between 14:00-15:30 and at 18:15 (between two larger peaks). However, there are continued spikes in network demand. There is no evidence that the two demand spikes related to the force charging of the 4 batteries. Therefore, the demand changes shown in household demand between 14:00-16:29 and 18:15-18:59 are masked and not clearly reflected on the phase demand comparison between price-driven and DNO-driven days.

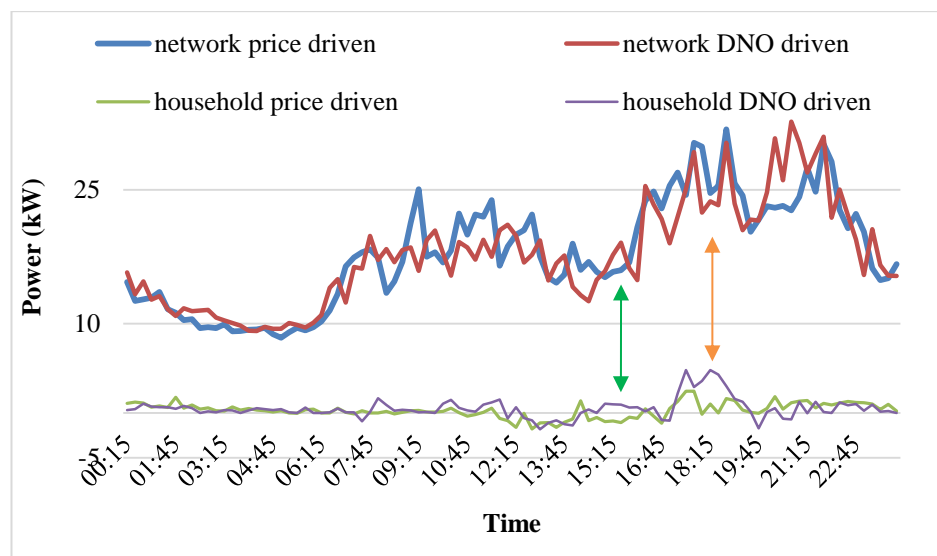


Figure 5-19 Network and household load profiles comparisons

The trial results can be summarized in table 5-8. The estimation is based on feeder 0021. The trial result shows that the demand change effect from households DSR system cannot be identified on the network level as expected.

Table 5-8 Quantification of percentage of DSR effect been masked at feeder 0021 phase 3 in network demand reduction trial

<i>Time of Day</i>	14:30-16:29	18:15-18:59
<i>Average demand change in households</i>	1.993 kW	3.067 kW
<i>Expected average demand change on substation feeder</i>	7.972 kW	12.268 kW
<i>Realistic average demand change on substation feeder</i>	2.170 kW	-0.365 kW
<i>Percentage of network demand change effect been masked</i>	72.8%	100%

As demonstrated in table 5-8, the households DSR system mainly brings demand change effect during two time periods (14:30-16:29 & 18:15-18:59). The average demand reduction effect across participated households are around 2 kW in period 1, and 3 kW in period 2. Considering there are 4 customers take part in DSR (penetration rate 6.6%) in phase 3, feeder 0021, the demand is expected to reduce about 8 kW and 12.3 kW during period 1&2. However, the realistic measurements show the demand reduction effect is critically masked by uncertainty. In period 1, 72.8% of demand reduction effect is masked, while in period 2, the effect is masked completely.

5.7.3 Masked effect of DSR on LV network

The DSR performance in households and network reveals that: 1) DSR can reduce peak demand for households by demand shifting; 2) the network demand does not reflect the effect of demand reduction or aggregated from households as expected. Therefore, this section discusses the causes of trial result qualitatively. In detail, the network demand uncertainty is firstly demonstrated and analysed. Then, the findings are demonstrated from a statistical point of view, to explain: 1) why demand reduction in individual households cannot make meaningful impacts on the network level; and 2) how network demand uncertainty impact the effect of network peak reduction.

A. Network Demand Uncertainty

The network demand data in the substation is analysed to obtain basic understandings on network demand uncertainty. A typical daily substation load profile is the aggregation of customers' load profiles connected under this substation. Since the customers' individual load profiles vary every day [126], the substation load profiles are uncertain between days as well. The driven forces behind these inherent uncertainties are various from weather conditions to customer uncertain behaviours etc.

Load profiles in the investigated substation, over one week are illustrated in figure 5-20; the load profiles of the one of the substation feeder are shown in figure 5-21. The black lines represent the weekdays' and blue lines represent the weekends' load profiles. The data is in 15 mins resolution. The figures demonstrate the uncertainty of network demand, and especially the uncertainty in feeder demand.

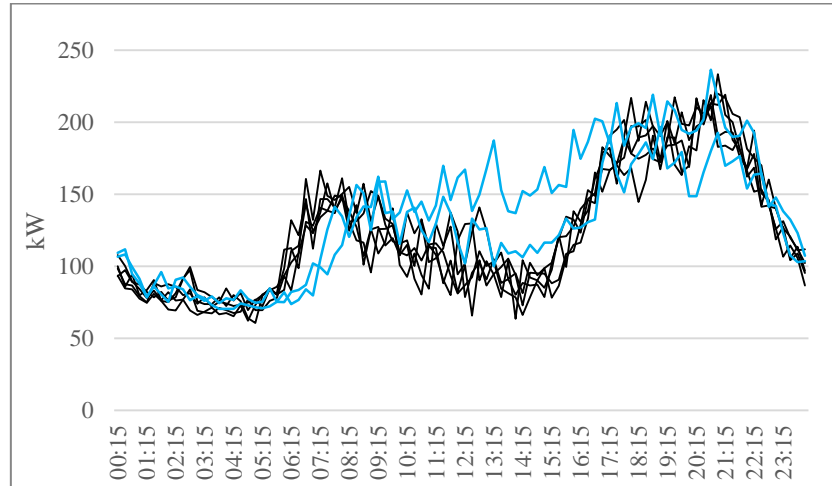


Figure 5-20 Network demand uncertainty in tested network

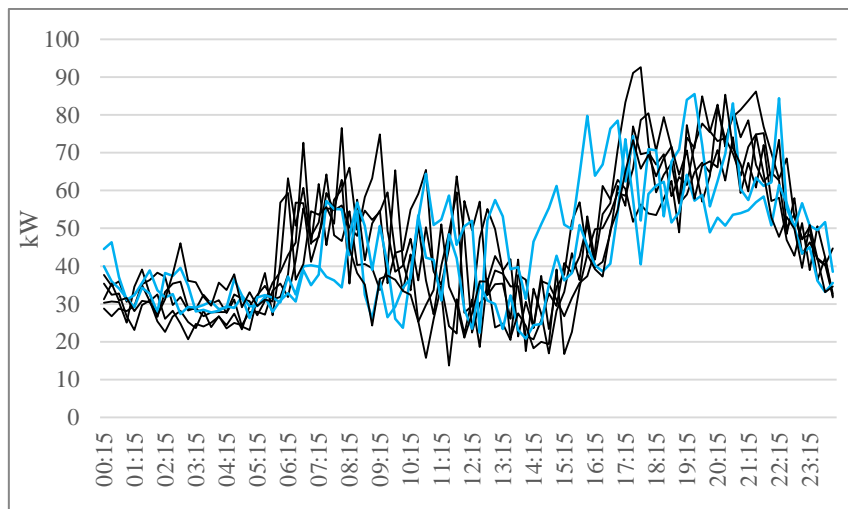


Figure 5-21 Feeder demand uncertainty in the tested network

To have a better quantitative understanding on networks' peak demand, the feeder's load profile is sliced to extract demand data during peak time. The peak time is chosen between 16:30-20:30. The discretely sampled peak demand value is collected on the feeder in the tested month, April in 2015. The bar chart shown in Figure 5-22 counts the frequency of peak demand, and presents the probability distribution. The cumulative distribution is shown in figure 5-23.

The result shown in figures suggests that: 1) the interval of peak demand is between 37 to 95kW; 2) in most of the days, the peak demands are concentrated between 48 to 88kW. The mean value is 64.74kW and standard deviation is 11.02kW.

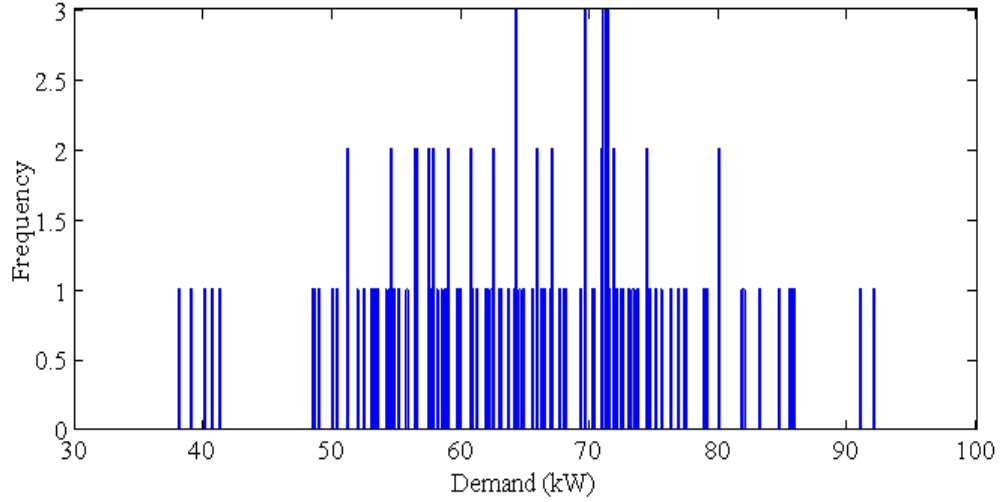


Figure 5-22 Demand distribution during peak time of tested network in April

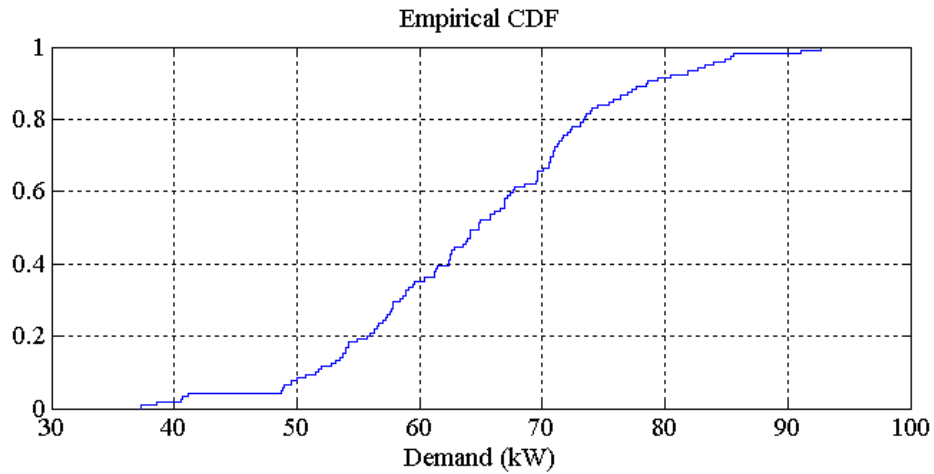


Figure 5-23 Cumulative distribution of demand in peak time of tested network in April

B. Uncertainty impact on network demand reduction

A bounded open interval is introduced as the representation of the sampled values of network peak demand. For the presence of uncertainty in network demand, the demand peak is not deterministic. The sampling of peak demand can be represented as a set of discrete values varies within a range. According to the properties of the set of interiors in Topology Theory [127, 128], network peak demand can be represented by bounded open intervals. Particularly, bounded open intervals are featured with supremum and infimum [127], which subjects the uncertain demand peak within this interval.

A typical bounded open interval S is shown in figure 5-24. The supremum and infimum boundary of interval S is noted as $\sup(S)$ and $\inf(S)$. Any demand peak value can be regarded as an interior point within bounded open interval S . According to Set Theory, the following theorem 1 [127] can be obtained accordingly.

THEOREM 1. For bounded open interval S . The set of its interiors is $Int(S)$. If bounded open interval T is the subset of interval S , then $Int(T)$ is a subset of $Int(S)$.

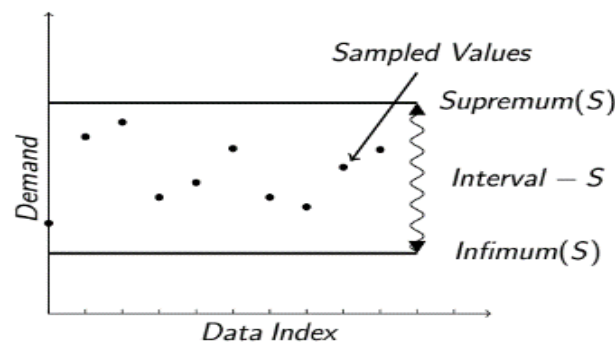


Figure 5-24 Open bounded interval for peak demand sampling values

The demand peak interval T over a time period is the sub-interval of the overall interval S , which represents the network demand peak for the substation. As shown in the figure 5-25, the supremum boundary, $\sup(S)$, and infimum boundary, $\inf(S)$, is subject to the demand peak of the whole substation. For a time period, the emerged demand peak values, noted as interval T , are included in a subset of interval S . This interval is featured with $\sup(T)$ and $\inf(T)$ to subject the boundary. Those boundaries could be any possible value as long as they follow the following inequality:

$$\inf(S) \leq \inf(T) \leq \sup(T) \leq \sup(S) \quad (5-16)$$

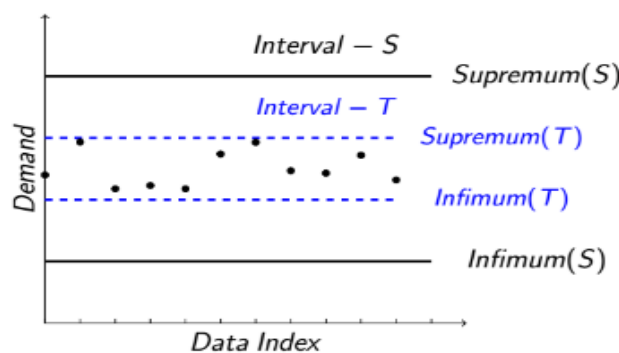


Figure 5-25 Peak demand sampling values during a period

With uncertainty incorporates, the effect of peak reduction contributed by

households to networks might be masked. The mask effect and its cause can be illustrated by comparing two extreme scenarios of sampled network peak demand shown in figure 5-26 and figure 5-27.

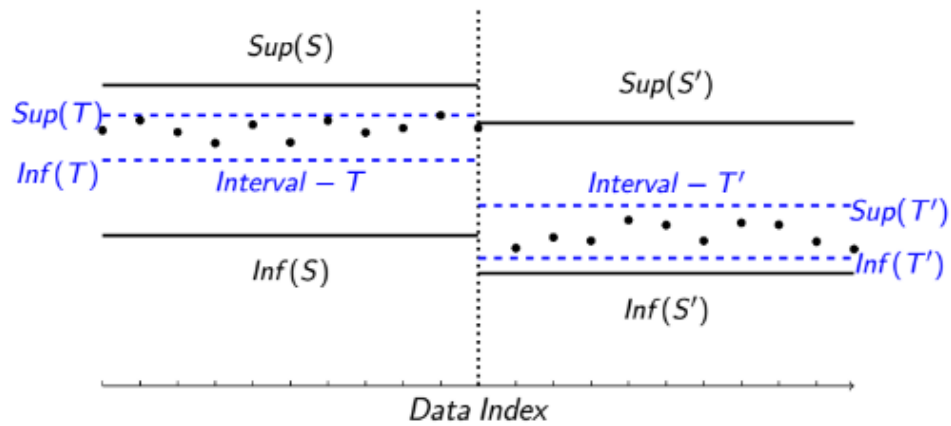


Figure 5-26 Visible effect of demand reduction

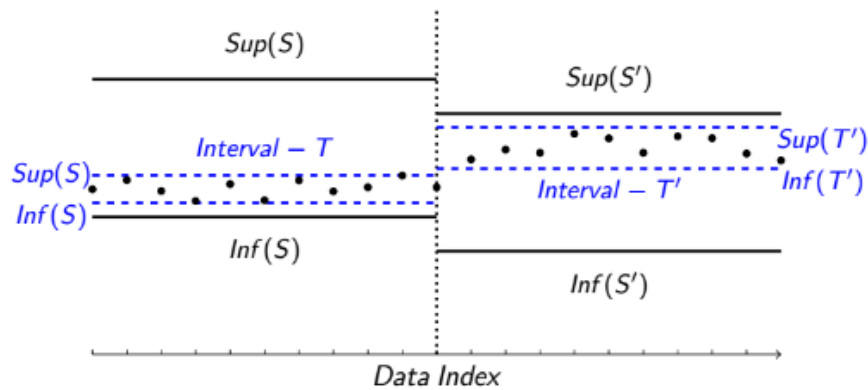


Figure 5-27 Masked effect of demand reduction

1. Desired scenario--Visible effect

Figure 5-26 shows one extreme scenario that the effect of demand reduction on networks can be visualised clearly. The interval T refers to the demand peak for a period before engaging DSR and interval T' describes that after DSR. In this scenario, interval T' is lower than interval T , in other words, the peak reduction brought by DSR is visible for the time period.

2. Undesired scenario--Masked effect

Figure 5-27 shows the opposite extreme scenario, the demand reduction is totally masked. The period demand peak interval T' is greater than interval T . This scenario

shows that the DSR effect in peak reduction cannot be identified within a limited time period. The less penetration of DSR, the higher probability that system peak reduction will be masked by uncertainty.

The DSR effect on peak reduction can lead to scenarios between the above two extreme scenarios. However, with more DSR effect on peak reduction, the effect of peak reduction on network demand is easier to be identified. On the contrary, without sufficient effect of peak reduction provided by DSR in households, the network demand uncertainty might mask the effect of peak reduction on networks.

5.8 Conclusions

This chapter propose a new optimization model for multi-functional EMS to maximize the customer benefits and respond to network request during certain peak time. The network request will be primarily fulfilled for whole system benefits. Additionally, the study for the first time provides an investigation on the realistic DSR performance on network demand reduction and discusses how the results are different from what are expected in the simulation.

The simulation results show that the multi-functional EMS could bring £1134 LV network investment deferral with 4.3% EMS penetration given the practical network utilization of 42%. However, when the EMS penetration increases to 12.5%, the network investment deferral will be £3038. Further, when the network utilization grow to 85% in the future, the network investment deferral could reach £10832. The customers' benefit reduces in this multi-functional EMS because of the reduced battery capacity utilization. Apart from reducing their own demand using battery, customers would export extra power to support network peak demand reduction. The customers located at the network with peak demand coincident with peak energy price will save more electricity bill, as 12.55% in the test network. The customers located at the network with peak demand at non-peak price time could only save 3.75% in electricity bill.

However, in the practical network trial, the DSR performance on increasing and

decreasing demand cannot be identified on networks. The invisible contribution from customers DSR to demand reduction at the network is caused by inherent uncertainty in network demand and relatively low DSR penetration. The demand uncertainties in network demand masks the demand reduction effect brought by DSR. For the purpose of meaningful demand reduction on network, the DSR penetration level should be sufficient to make a real impact.

Chapter 6. Quantification of DSR Volume for Meaningful Network Impact

Chapter 5 have discovered that the realistic DSR performance on increasing and decreasing demand cannot be identified on networks. The relatively low penetration of DSR and the uncertainties in network demand easily mask the demand reduction effect. The network operators' benefit cannot be delivered if they cannot experience any impact of DSR. Therefore, this chapter of the thesis investigates how much DSR penetration is required to reduce the network demand given the inherent uncertainty. The meaningful DSR demand reduction is proposed from statistic point of view and results of the DSR penetration are given based on the confidence level of peak demand reduction.

6.1 Introduction

To validate the efficacy of DSR performance on network demand reduction, majority of the previous researches estimated the demand reduction effect by cumulating simulated demand from households [34-36, 129, 130]. In these literatures, the network demand was assumed to be deterministic so that the demand reduction on network can be assessed easily by summing up the individual DSR contributions of each engaged households. On the other hand, a few study analysed the demand reduction effect at whole system level using normalized measured network demand data [131]. As a consequence, even a minor demand reduction effect from household DSR can be entirely reflected at network side in their assessments.

However, in reality, there is inherent uncertainty in network demand, i.e. network demand changes each day and has many spikes at different times. With this uncertainty involved, the network demand can be located within a certain interval, rather than deterministic. After DSR employed, if network demand is higher than before, the demand reduction effect of DSR is offset. Thus, the household aggregating effect of network demand reduction may not be able to be transferred to the network level. Without considering network demand uncertainty in practice, the previous cumulating and normalizing approaches are not accurate to assess DSR performance on network demand reduction.

Yet, few study has investigated the uncertainty in network and analysed its significant impact on performance of DSR. Therefore, this research is to determine the

required DSR penetration to result meaningful network demand reduction under practical uncertainty impact. For the distribution system operators and generators, the proposed approach gives them the essential visibility and benchmark of DSR penetration that helps them to optimize the investment of DSR.

This chapter for the first time presents a quantitative analysis on meaningful DSR demand reduction on LV networks under realistic scenarios. A probability-based data-driven quantification method is proposed to quantify the minimum required DSR penetration for concrete network demand reduction. In detail, the chapter firstly addresses the masked demand reduction problem in a LV network in Southwest, UK [59]. The results of the trial in the last chapter confirmed that there are inherent uncertainties in network demand and this demand uncertainty masks the demand reduction effect when DSR penetration is low. The actual network demand considering uncertainty is defined using average value and distribution in statistics. Then the concept of meaningful network demand reduction is proposed from a statistical calculation. And the “divide-and-conquer”[132, 133] strategy, widely used in computer science, is adopted in the data driven algorithm to implement the proposed method and simplify the complex calculation process. The effectiveness of the proposed method has been validated on a LV distribution network located in the southwest of UK. Time and location influences on minimum required DSR penetration rate are illustrated with sensitivity analysis.

The rest of chapter is organized as follows: Section 6.2 introduces a new method to quantify how much DSR is required for meaningful demand reduction; Section 6.3 demonstrates practical case studies and provides a sensitivity analysis on required demand reduction, reduction time and location; Section 4.6 draws the conclusion.

6.2 Methodology

The main purpose of this study is to investigate the minimum required DSR penetration rate to ensure the required meaningful network demand reduction at peak demand time. The inherent uncertainties of network demand may mask the demand reduction effect contributed by household DSR when the penetration rate is relatively

low. In order to make concrete impact on the network demand reduction, the DSR penetration should be sufficient to immune against the inherent network demand uncertainty. The quantitative relationship between the confidence level of meaningful network demand reduction and required DSR penetration is analysed in this section.

6.2.1 Concept of meaningful network demand reduction

According to the interpretation of masked effect on peak demand reduction, this study proposes the concept of meaningful network demand reduction and minimum required DSR volume:

Definition 1: meaningful network demand reduction: refers to a probability guarantee at level of confidence α to achieve Δ network demand reduction.

Definition 2: minimum required DSR volume: $R(\alpha, \Delta)$ refers to minimum required reduction effect, which is equivalent to DSR volume, to achieve meaningful network demand reduction with parameters (α, Δ) . This demand reduction can be converted into minimum required DSR penetration rate.

The level of meaningfulness is measured by the confidence level α . For example, the meaningless demand reduction is equivalent to 50% demand reduction confidence level (0% DSR penetration) and the entirely guaranteed demand reduction (100% meaningful network demand reduction) is equivalent to 100% demand reduction confidence level. The minimum required DSR volume is the aggregating demand reduction contributed by household DSR systems

6.2.2 Algorithm to decide minimum required DSR penetration

A. Algorithm theoretical basis

Probability Theory [134] is introduced as the theoretical basis to calculate the minimum required DSR volume, $R(\alpha, \Delta)$. It is assumed a bounded open interval S describes the original network demand peak before DSR and interval S' describes the new peak demand. As shown in figure 6-1, the function $f(x)$ represents the probability density function (PDF) of network demand peak interval S , with supremum and infimum, $\sup(S)$ and $\inf(S)$. The function $f'(x)$ represents that of new demand peak

interval S' . The relevant supremum and infimum is $\sup(S')$ and $\inf(S')$.

The probability distribution within interval S' is assumed to be identical as the distribution in interval S , i.e. the reduced peak demand interval S' is the translation of original interval S . The physical meaning is the household DSR systems change the load profiles during the peak time by reducing the demand magnitude but not the load profiles' shape. It is assumed that the DSR demand reduction effect will not bring additional uncertainty to the network demand. Given certain DSR demand reduction to network, the mean value of the peak demand distribution will change while the shape of the distribution will stay as the same.

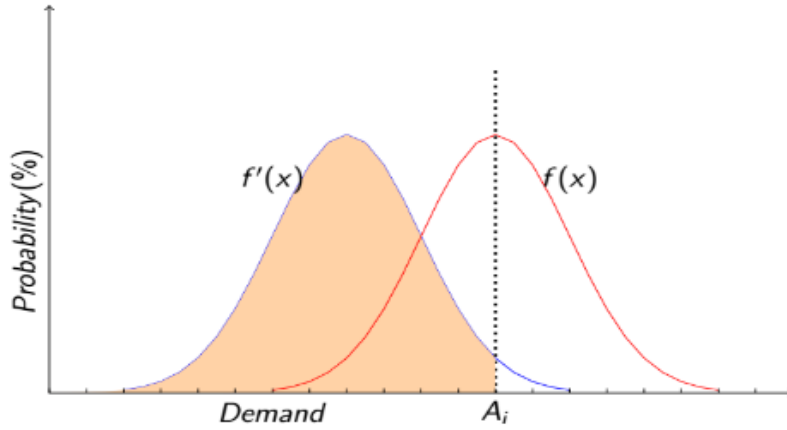


Figure 6-1 Probability that DSR can reduce network demand given the knowledge of a demand sample A_i

When there is demand reduction, the sample of reduced demand is expected to be lower than original demand by Δ . Assuming the sample in interval S and S' is noted as A, A' , this probability proposition can be represented by B in equations 6-1 and 6-2:

$$B: A' < A - \Delta \quad (6-1)$$

$$B = \{ \text{sample of reduced demand is lower than that of original demand by } \Delta \} \quad (6-2)$$

The condition of achieving meaningful network demand reduction is that the confidence level of this probability event is equal or larger than the target confidence level α . This condition can be shown as:

$$Pr\{B\} = Pr\{A' < A - \Delta\} \geq \alpha \quad (6-3)$$

The events $A_1 \dots A_n$ form a partition of the whole sample space $Int(S)$, the probability event A_i is defined as:

$$A_i = \{ A \text{ sample from original demand} \} \\ \text{for } i = 1, \dots, Card(Int(S)) \quad (6-4)$$

According to Total Probability Theorem [135] shown in equation 6-5, the probability that the new samples are lower than the original samples by Δ can be calculated with formulation equation 6-6:

$$Pr\{B\} = \sum Pr\{B|A_i\} * Pr\{A_i\} \quad (6-5)$$

$$Pr\{A' < A - \Delta\} = \sum_{A_i \in S} Pr\{A' < A - \Delta|A_i\} * Pr\{A_i\} \quad (6-6)$$

Where $Pr\{A_i\}$ refers to the priori probability distribution of network demand peak (probability of A_i happens), as shown in Figure 6-1. This network peak demand probability distribution can be obtained from historical data. $Pr\{A' < A - \Delta|A_i\}$ refers to the conditional probability that peak reduction is meaningful in the condition of sample A_i .

Therefore, the minimum required DSR volume, $R(\alpha, \Delta)$, is calculated to guarantee the following inequality:

$$\sum_{A_i \in S} Pr\{A' < A - \Delta|A_i\} * Pr\{A_i\} \geq \alpha \quad (6-7)$$

The minimum required DSR volume, $R(\alpha, \Delta)$ is the translation distance between interval S and S' .

B. Data-driven Algorithm

A data-driven algorithm based on the binary search algorithm [136] is adopted to find the minimum required DSR volume as shown in figure 6-2, and the relevant pseudo code is presented in Algorithm. 1. In general, there are three main stages in this binary search algorithm:

Algorithm 1: Calculating minimum required DSR penetration

- 1: Read network demand sampling value set \aleph .
 - 2: Sort the set \aleph with ascending sequence.
-

```

3:   Define demand reduction range  $\Lambda = [\Lambda^{lo}, \Lambda^{up}]$ ,
   initialize  $\Lambda_0$  as  $[0, \max(\aleph) - \min(\aleph)]$ .
3:   Repeat
4:     At  $k^{th}$  times of iterations Do:
5:       Estimate  $R(\alpha, \Delta)_k$  as  $\frac{\Lambda_k^{up} + \Lambda_k^{lo}}{2}$ .
6:       Calculate the confidence level  $\alpha_k$ 
7:       If  $\alpha_k > \alpha_0$  (target confidence level) Then
8:         Update  $\Lambda_{k+1} = [\Lambda_k^{lo}, R(\alpha, \Delta)_k]$ .
9:       Else if  $\alpha_k < \alpha_0$  Then
10:        Update  $\Lambda_{k+1} = [R(\alpha, \Delta)_k, \Lambda_k^{up}]$ .
11:      End
12:    End
13:  Until confidence level  $\alpha$  approaches target
  confidence level  $\alpha_0$  under error tolerance  $\varepsilon$ .
14:  Calculate minimum required DSR penetration
  rate based on minimum required DSR
  volume  $R(\alpha, \Delta)$ 
15: Terminate

```

- 1) Data preparation: In the stage, the sampled value of network demand during peak time are obtained from smart metering data, and stored in set \aleph . Then sort the set in ascending. Therefore, the range of demand reduction is $\Lambda = [0, \max(\aleph) - \min(\aleph)]$.
- 2) Loop at k^{th} times of iterations: give an estimate on required demand reduction as $R(\alpha, \Delta)_k$ according to demand reduction range Λ_k ; calculate the confidence level α_k at the condition of given demand reduction $R(\alpha, \Delta)_k$; compare α_k with target confidence level α_0 , then modify the parameters Λ_k into Λ_{k+1} for $k + 1^{th}$ times of iteration.
- 3) DSR penetration calculation: when the terminate condition for iteration loops in 2nd step meets, calculate minimum required DSR penetration rate according to the minimum required DSR volume $R(\alpha, \Delta)$.

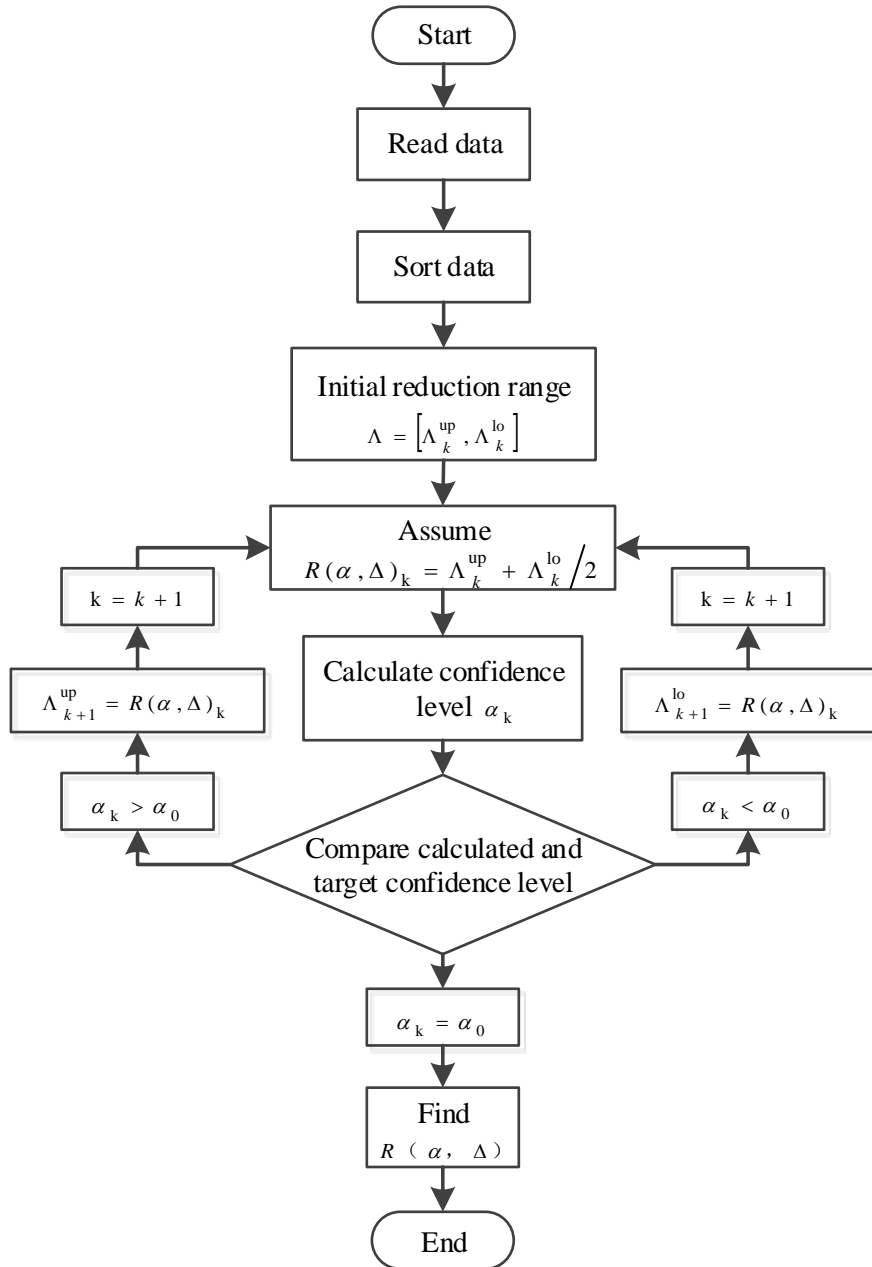


Figure 6-2 Flow diagram of data drive algorithm

6.3 Demonstration

This section investigates the minimum required DSR penetration for achieving meaningful network demand reduction and examines the influence of differing time and location. In detail, 1) minimum required network peak reductions for examined networks are calculated and converted into minimum required DSR penetration rate for make impact; 2) sensitivity analyses are conducted on different amount of target demand reduction Δ , different time and different network locations.

6.3.1 Minimum required DSR volume

In this section, feeder 1 (feeder 0011&0012), as shown in figure 6-3 in selected substation used in chapter 5 is taken as an example to demonstrate how to determine minimum required DSR volume under realistic scenario. The measured data of feeder 1 are analysed to gain the basic understandings of network peak demand distribution. The demand distribution during peak time in January is presented in figure 6-4. The demand peak time included in this work is chosen between 16:30-20:30. In tested feeder 1, the range of peak demand is between 70 to 160kW. While in most of the days, this range of peak demand concentrates between 90 to 130kW.

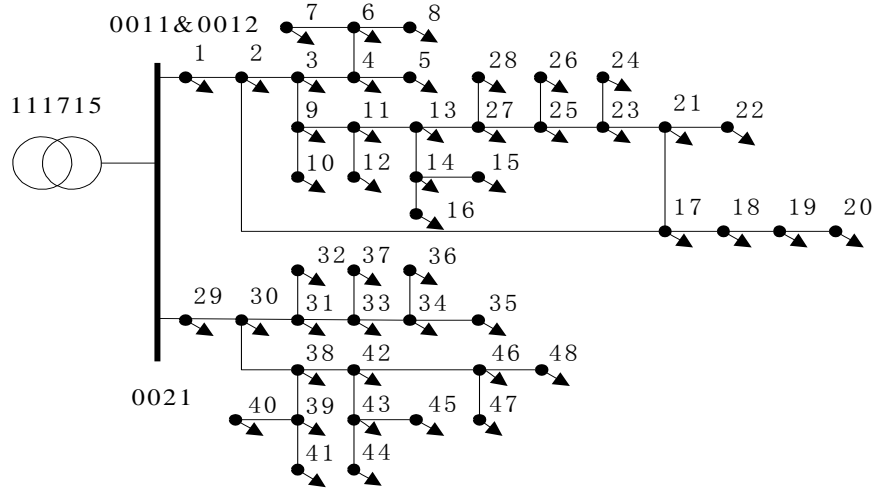


Figure 6-3 Substation layout

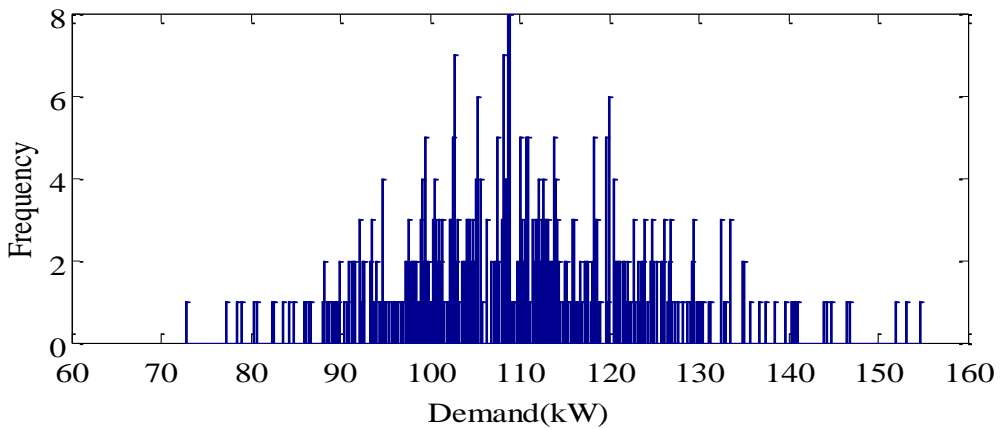


Figure 6-4 Demand distribution during peak time

Using proposed data-driven algorithm, the relationship between the minimum required DSR volume(α, Δ) and the confidence level α is calculated. The parameter Δ is set to be 0.

The result is shown in the figure 6-5. The curve shown in figure 6-5 reveals that how the minimum required DSR volume (Y axis) varies for guarantees of differing confidence level (X axis). In other words, there is Y (kW) effect demand reduction required from household DSR systems in order to guarantees X confidence level that the sample of reduced network demand is Δ (kW) lower than samples of original network demand. Specifically, the two extreme points: (0.5,0) and (1,83), represent the situation when: 1) the sample from new network demand have 50% probability (at 50% confidence level) lower than the sample from original network demand, when there is no household DSR contributes (0% DSR penetration rate); 2) the sample from new network demand is 100% lower than the sample from original network demand when household DSR can provide 83kW aggregating effect of demand reduction to the network. There is a sharp increase of battery-bring demand reduction when confidence level is larger than 97%, from 36kW to 83kW. Particularly, when there is 95% confidence level to guarantee decreased new network demand, the minimum required DSR volume is only 31kW. Compared with 83kW effect from DSR to achieve totally meaningfulness of demand reduction, the required DSR-bring demand reduction for guarantee of 95% confidence level is only one third (31kW) of that in 100% confidence level

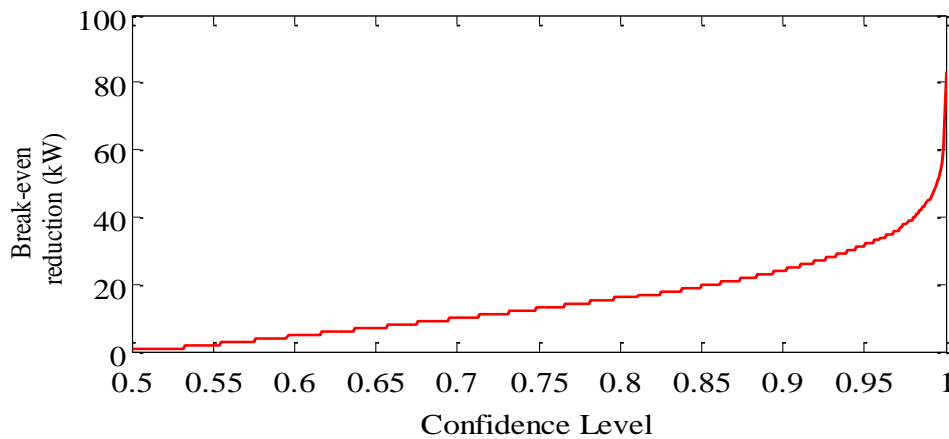


Figure 6-5 Minimum required DSR volume at different confidence levels

Given the DSR parameters and 4 hours peak demand time, 37 and 99 household DSR systems are required to be installed to guarantee at least Δ (kW) ≈ 0 (kW) of network demand reduction at 95% and 100% confidence level.

6.3.2 Sensitivity analysis

Sensitivity analyses are conducted to investigate the impacts from different: 1) target amount of network peak demand reduction; 2) time and 3) network locations on the choice of DSR penetration rate.

A. Target amount of network peak demand reduction

Figure 6-6 shown below gives the differences of demand reduction required for different target amount of reduction Δ (Delta) of peak demand reduction. When Δ equals to 0, the expected network demand is just less than the original demand; when Δ equals 5 or 10, the expected new demand is less than the original for 5 or 10 kW. Under 95% confidence level, the minimum required DSR volumes are 31kW, 36kW and 41kW respectively. Particularly, 37, 43 and 49 household DSR systems are needed. The increase of minimum required DSR volume is equivalent to the increase of Δ . Figure 6-7 shows that the minimum required DSR volume and Δ have a linear relationship with the ratio of 1.

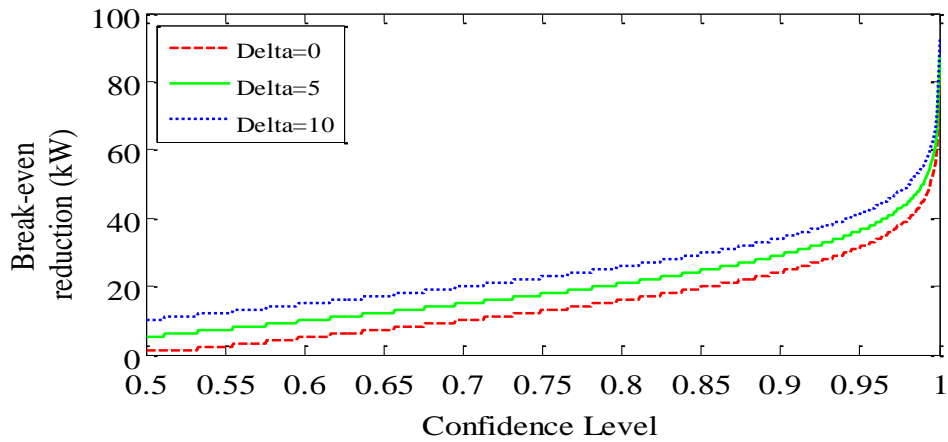


Figure 6-6 Minimum required DSR volume of different deltas

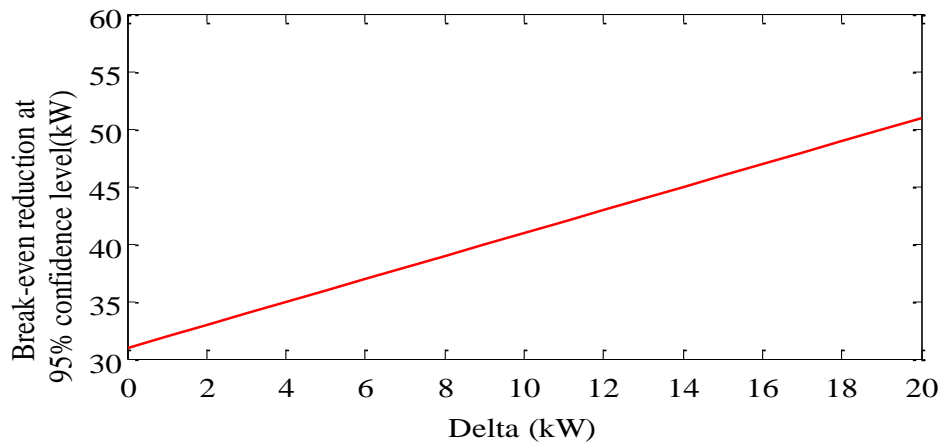


Figure 6-7 Relationship of minimum required DSR volume reductions and deltas

B. Time

Figure 6-8 shown below gives the difference of demand reduction required for three different months: January, February and April. The results show that there is minor difference between minimum required DSR volume curves for the tested three months, which may indicate that the time impact is less influential. At 95% confidence level, the minimum required DSR volumes for the three months are 31kW, 30kW and 29kW respectively. In this case, 37, 36 and 35 household DSR systems are required. However, at 100% confidence level, the minimum required DSR volumes are 83kW, 80kW and 68kW, which, the results between January and February is close and the difference between April and January/February are large.

The peak demand distributions of three months are shown in figure 6-9. The relationship between the three peak demand distributions is similar with the relationship of three months' minimum required DSR volume at 100% confidence level. Generally, the distributions are close between January and February, ranging between 70kW to 160kW. The overall demand of January is slightly higher than February--the demand higher than 100kW in January is more common. However, the maximum peak demand happens at February. The network peak demand of April is much less than January and February, ranging from 50kW to 120kW. Even the demand is quite different, the general trend of peak demand distribution are similar.

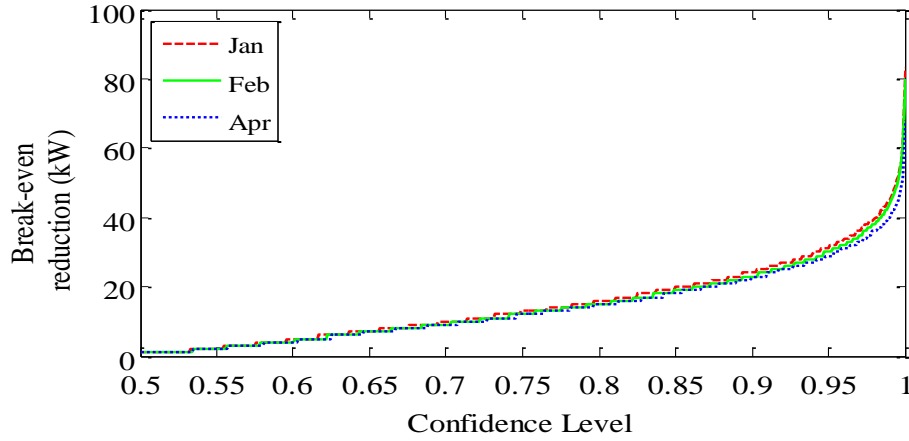


Figure 6-8 Minimum required DSR volume of different months

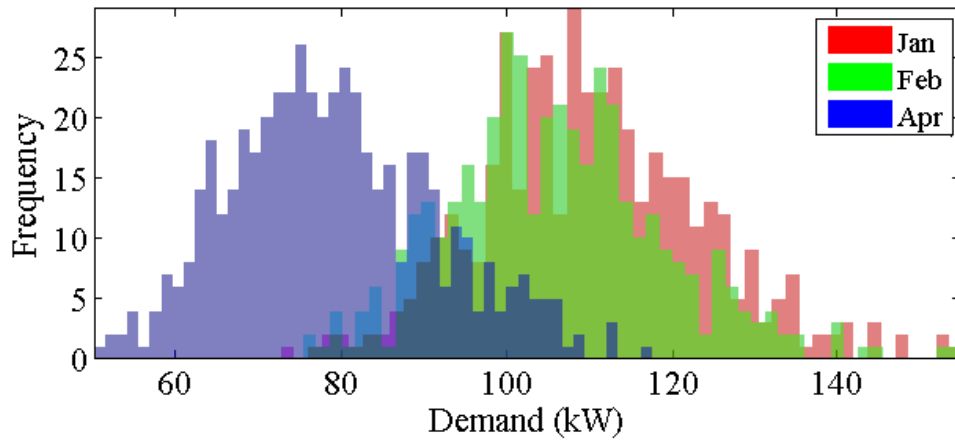


Figure 6-9 Peak demand distributions of different months

C. Network location

Figure 6-10 gives the differences of minimum required DSR volume for different locations. Location 1 is the base case in previous section 6.3.1. As a comparison, 1) location 2 is the feeder 2 (feeder0021) of the substation 1 in figure 6-3; 2) location 3 is the feeder 1 of another substation which is 0.8km away. The demand reduction requirement in location 2 is slightly lower than location 1. The minimum required DSR volume in location 3 is much smaller. At 95% confidence level, the minimum required DSR volumes for the three locations are 31kW, 30kW and 17kW respectively. In other words, 37, 36 and 20 household DSR systems are needed. At 100% confidence level, the minimum required DSR volumes are 83kW, 77kW and 41kW. In location 3, the minimum required DSR volume at 100% confidence level is nearly half of location 1 and 2.

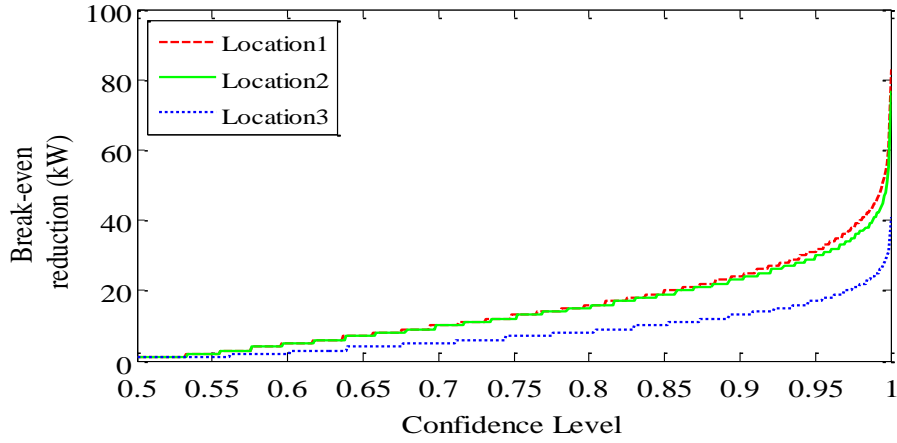


Figure 6-10 Minimum required DSR volume of different locations

The comparison of peak demand distribution is shown in figure 6-11. It should be noticed that although the required reduction of location 2 is smaller than location 1, the overall peak demand of location 2 is larger than location 1. However, in location 2, the peak demand interval is narrower, from 90 to 170kW, which means the samples of peak demand are more concentrated. In location 3, the peak demand interval is smallest and narrowest. The peak demand in location 3 is generally half of that at location 1 and 2, ranging from 30kW to 70kW.

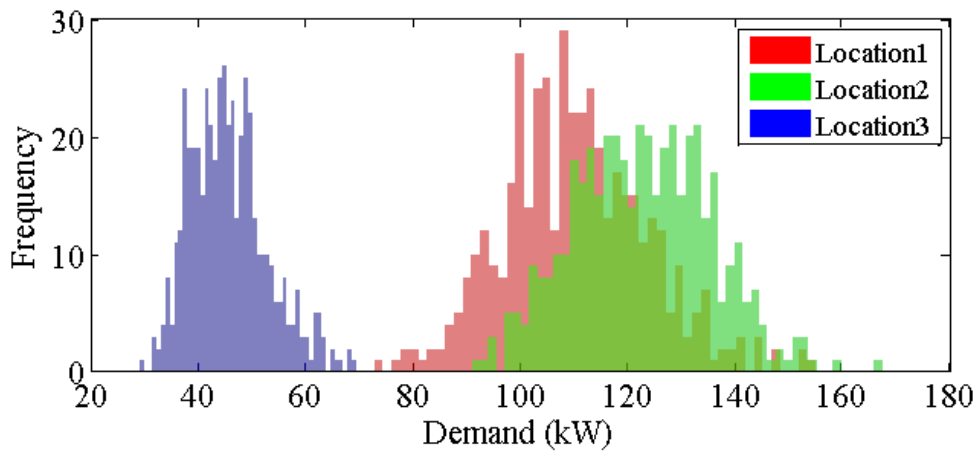


Figure 6-11 Peak demand distributions of different locations

6.4 Conclusions

This chapter proposes a new concept of the minimum required DSR penetration rate to guarantee concrete and meaningful network peak demand reduction. The DSR

penetration is represented by the total amount of demand reduction effect brought by household DSR systems, i.e. minimum required DSR volume. A probability-based data-driven method is proposed to calculate minimum required DSR volume and related DSR penetration rate. Examined on practical scenarios, the result shows that 1) to guarantee network peak reduction at 95% confidence level, the minimum required DSR volume is only around 15-25% of network peak demand; 2) to guarantee 100% confidence level, the minimum required DSR volume significantly increases 50% of network peak demand; 3) at the given confidence level, the amount of minimum required DSR volume is proportional to the guaranteed amount of peak demand reduction; 4) the amount of minimum required DSR volume is relatively stable over different months and 5) the amount of minimum required DSR volume highly depends on network locations.

Chapter 7. DSR Management for Local and Central Energy Market

Commercial tools and market mechanisms are recognised as one of the most effective solutions to address today's energy challenges. For example, efficient markets designed at both local and regional levels can largely facilitate adoption of renewables and incentivise customer's engagement in the general energy market. This chapter of this PhD thesis quantifies DSR benefits with the presence of both central and local energy markets. Aiming to facilitate the development and implementation of various on-going market concepts, this section provides one possible market formulations in the future with the imperative input of the DSR value quantification.

7.1 Introduction

The future energy system will see an increasing number of flexible demand and distributed renewable generation connected in the distribution networks. The prospective demand increase and bi-directional power flow will bring severe network pressures in terms of thermal and voltage violations. However, at the same time, the rapidly advanced information and communication technologies is empowered to distribution networks. The distribution network soon would be a highly informative and dynamic network infrastructure.

Apart from technology method that mitigate the adverse impact brought by distributed renewable generation and low carbon flexible demand, commercial tools and market mechanisms are important components in addressing these challenges. An effective commercial strategy could change the traditional roles of stakeholders and create new roles and opportunities in the power system and thus encourages every individual in the system to change the behaviours such that reduce the uncertainty in the low carbon network and increase the benefits for the whole system.

The local energy market is a natural derivative new commercial product from increasing local generations, local flexible appliances and advanced metering and communication technologies. Local energy market offers direct commercial benefits to customers that match local demand to local supply, offers the prospect of reducing flows to and from the distribution networks, and thus mitigating the thermal and voltage violation problems [137]. Additionally, local energy market could enable niche markets aligned to local concerns and communities. On the contrary, the local energy market

would encourage more integration of renewable generation and DSR to further improve the low carbon process.

There are three main streams of researches that investigate the local energy market at present. The first stream is to investigate the market structure in the local energy market. The authors in [138] propose a local market setup for both traditional and new stakeholders in the power system. The salient features in the setup include a pricing model encourages local trading and a decision-making system for bid and ask matching. The authors in [139] propose a local energy market structure to facilitate and manage the electricity trading between the citizens of a smart city. The implied aim is to use the local energy market to achieve market-driven DSR. The proposed NOBEL market is based on the stock exchange model, with the difference that the trading periods are discrete fixed time slots. The local market is simulated and proved to be a viable approach as a DSR to help address the network problems. The study in [140] also proposes a local market layout to integrate market and technical solutions to coordinate distributed energy resources (DERs). The work focuses on identifying the characteristics of the participants, degree of competition, trading horizon and dispatch intervals and market mechanisms.

The second stream focuses on the system equilibrium in the local energy market. The core of these system equilibrium studies is to design the distributed control while to achieve whole system balance. Specifically, the authors in [141, 142] develop non-cooperative games for customers to minimize the individual electricity bill while achieve the whole system equilibrium. The study in [143] proposes a distributed “power match” algorithm. The algorithm simulates the “bid and ask” process from consumer and producers, balances supply and demand per the business case and return a market clearing price to the local energy market. The authors in [144] propose an agent-based application to deal with the negotiation among different parties producing and consuming energy. The aspects like balancing, pricing, especially negotiation and adaptation in the local energy market is implemented and discussed. The concept of “minority game” and “stochastic game” are designed in the negotiation process to achieve whole system trading equilibrated.

Based on the price and load characteristics, the third stream is to develop optimal energy management for aggregators/DSOs in the local energy market. The authors in

[145] propose an optimal energy consumption scheduling for local trading centre (aggregator). Two modes of the local trading centre are investigated: 1) the non-profit-oriented centre, which aims to benefit energy consumers and sellers; and 2) the profit-oriented centre, which aims to maximize its own profit while ensure the required net-gain for energy consumers and sellers. The authors in [146] develop a hierarchical optimal bidding strategy for DSO to procure flexibility in the local energy market. It minimizes the cost of for DSO to bid for flexible demand and determines the DSOs' bid price to participate in the ahead markets and real-time dispatching.

This chapter proposes a new MILP based optimal DSR management model for individual customer within central and local energy markets. The proposed model determines most profitable DSR trading opportunities for customer when receiving the price information from both markets. The customers demand, generation, storage capacity, and several price signals, including sell and buy prices in both energy markets, are input into the optimization model. Different trading scenarios are transferred as 0-1 integer models and the optimal trading behaviours are derived from MILP. In the proposed DSR management model, a certain market arrangement is assumed. Customers could buy electricity from both central and local markets but could only sell electricity to local energy market. With different types of LCTs, customers could offer different electricity selling prices. At each trading period, each customer either bid or offer. It is assumed the energy trading platform is available and the model targeted customers could trade successfully with the ask/accept price in the optimization model. However, based on the optimal DSR management results, the feasible and reasonable ask and accept prices for different types of customers are discussed in detail.

The rest of chapter is organized as follows: Section 7.2 gives an overview of central and local energy market arrangement; Section 7.3 introduces the local market participants in the proposed local energy market structure; Section 7.4 develops an optimal EMS for customers in the local energy market; Section 7.5 illustrates the problem formulation; Section 7.6 demonstrates the trading behaviour of different customers under different central and local prices derived from optimal trading EMS; the model with traditional model and Section 7.7 draws the conclusion.

7.2 Central and local energy market arrangement

Traditionally, the electricity is generated from large scale generation plants, delivered from transmission to the distribution network and then to customers in a unidirectional way. The existing energy market of UK and some EU countries consists of five main participants: generators, transmission system operators (TSOs), distribution network operators (DSOs), suppliers (retailers) and customers. The wholesale energy market was built in each country for energy trading between generators and retailers. Therefore, the money flows are bottom up. The energy costs flow back to generators and network charges flow back to network operators. There are traditionally two money flow paths. In the first mode, “One bill mode”, as shown in figure 7-1, customers receive only one bill from supplier stating the charges from all the other participants. The UK is one of the typical countries adopting this business relationship. In contrast, in the second mode, i.e. the “Two bills mode”, as shown in figure 7-2, customers receive bills from supplier and DSO respectively stating the energy cost and transmission and deliver cost respectively. Finland is one of the typical countries using this business relationship.

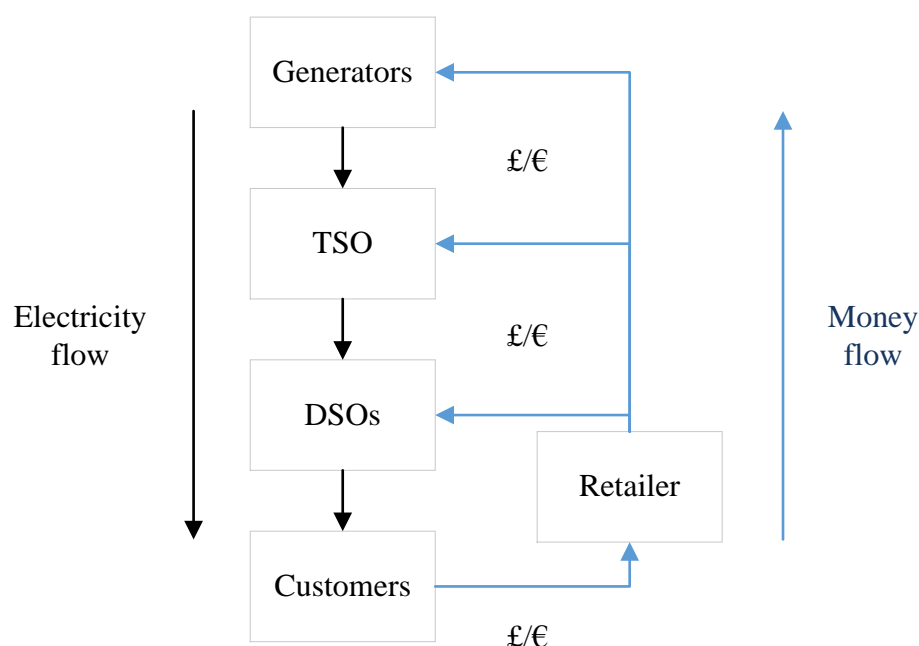


Figure 7-1 Market participant connections under “one bill mode”

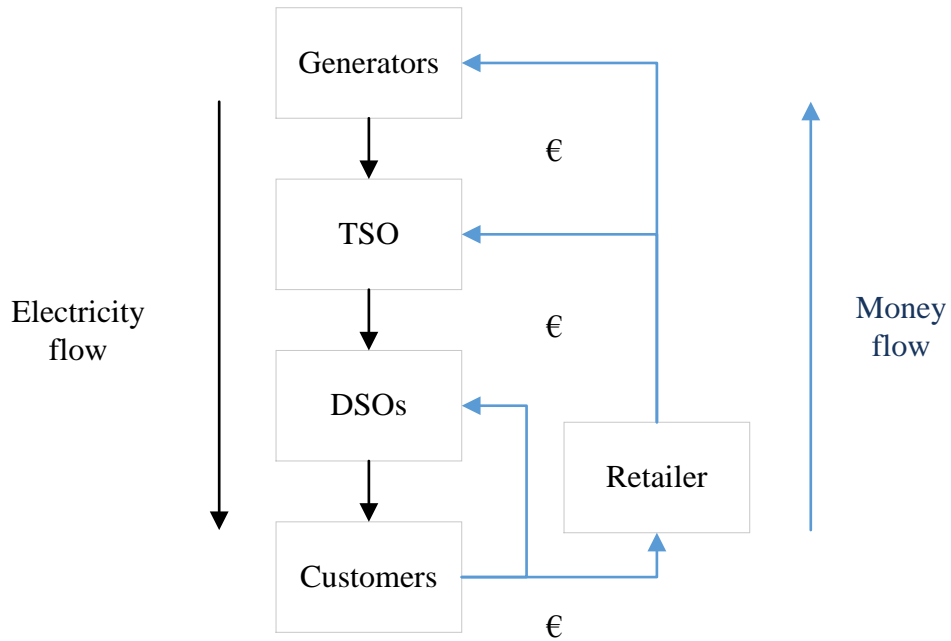


Figure 7-2 Market participant connections under “two bill mode”

However, recently, an increasing number of distributed energy resources, such as PV, distributed wind turbine, EV or battery are being connected to the distribution network and premises of customers. More important, it is estimated that distributed renewable energy sources are sufficient to fulfil a large portion of electricity demand [147]. Therefore, in this new low carbon environment, there will be new market participants, such as aggregator and energy service companies (ESCOs) [148], and the roles of the existing participants need to be evolved. For example, the role of the owners of the distributed energy resources in the energy market could change from consumer to both consumer and producer. Therefore, the original vertical energy market could change to a “crossing” energy market, i.e. the energy trading is both vertical and horizontal as shown in figure 7-3. Instead of only one wholesale market, there will be an additional local energy market, in which, the customers with distributed energy resources, with or without the help of ESCOs (including aggregators) could buy and sell electricity freely.

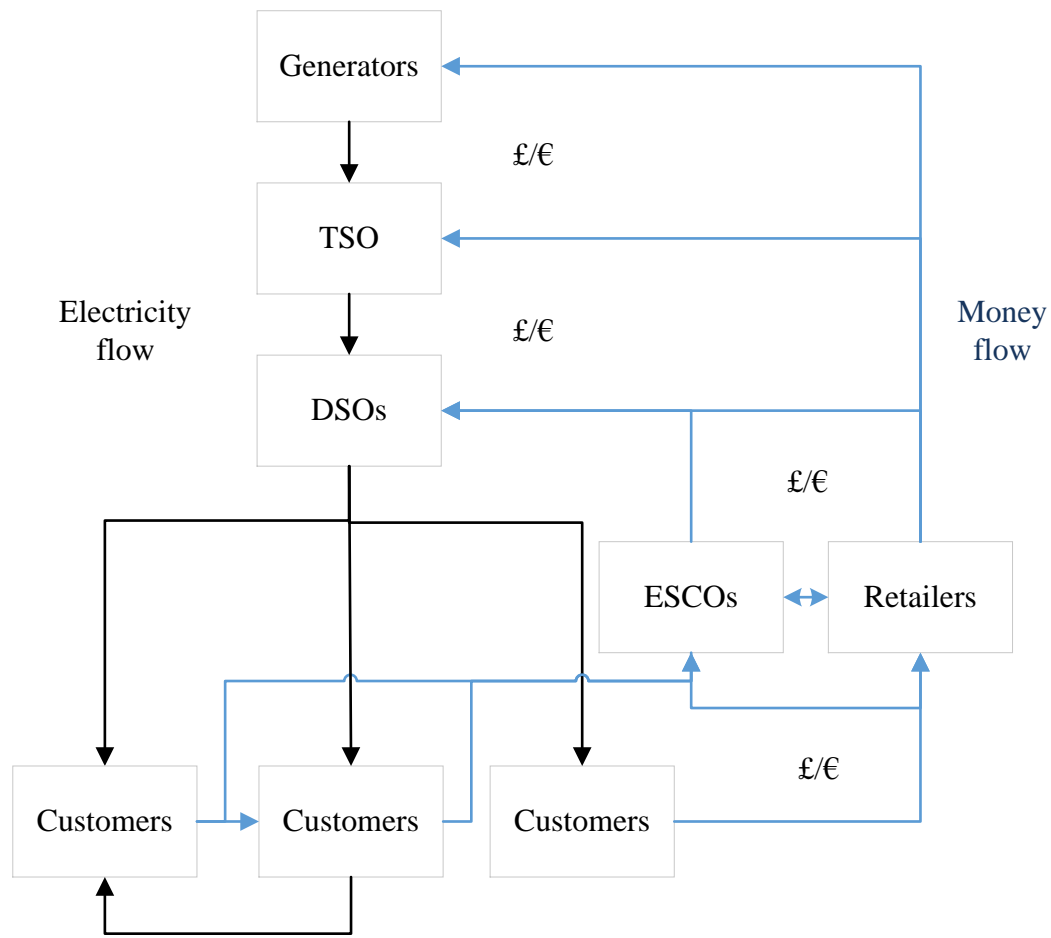


Figure 7-3 New market structure

In order to facilitate this system operation and local energy trading, control approaches of both whole system balance and coordination, and local energy resources, are required. The whole system control systems need to guarantee network reliability and security and coordinate the distributed energy resources among the whole system to maximize the benefit for network. The local energy resources control system is to manage trading behaviours to maximize the market participants' benefit. At the same time, the communication systems are required to link the local and whole system control system. This part of the thesis proposes a local energy resources control system to optimize trading behaviours.

The local energy market is supposed to bring cheaper electricity or reliable back up as an electricity compensator of central energy market.

7.3 Local energy market participants

In this section, a complete overview of the participants in local energy market and their potential energy trading behaviours are summarized.

- Trading platform operator:

In either centralized local energy market or distributed local energy market, at least one trading platform is needed. In this study, it is assumed both short term trades, i.e. auctions, and long-term trades, i.e. bilateral trading are available. The bid and ask information including the price and quantity, is exchanged on the platform. Customers could choose to take part in both auction price match mechanisms, i.e. uniform price system or discriminatory price system [149], or make bilateral agreements beforehand. The uniform clear price information can be found on trading platform. And for discriminatory price mechanism, the bid and ask information is listed on the trading platform.

- DSO:

Distribution network operators guarantee the network reliability and security. They have the rights to monitor and control (stop) all the trades, both short term and long term. Therefore, the auction information and bilateral agreement information are submitted to DSO for network reliability purpose.

- Buyers:

Customers with flexible demand are most likely to be the buyers in local energy market. Nowadays, the heat related “controllable loads”, including micro-CHP and heat pump are replacing traditional gas/oil-fired heating systems in the households [39, 150-153]. Additionally, increasing number of the customers choose the electric vehicles [154, 155]. The report [156] points out that the global electric cars on the road have exceeded the threshold of 1 million, closing at 1.26 million at the year of 2015. The demand for controllable loads and EV charging are elastic and less-reliability required most of the time. These flexible demands deserve cheaper price with the ability of absorbing excessive renewable power and reducing network usage. The customers with

flexible demand could search cheap supplies in the local energy market for a specific time interval.

- Sellers:

Customers with cheap generator are ideal sellers in local energy market. Recently, “Feed-in-Tariff”, which was used to encourage renewable generation penetration by governments, is gradually ceased in several countries [15, 25, 157]. For customers’ sustainable profitability in the future, the excessive renewable energy could be sold to others who needed in the local energy market. Additionally, the generated renewable electricity at customers’ has competitive advantage -- low price, over electricity generated from traditional large-scale power plants. Firstly, the cost of renewable generation, like PV and wind turbine, is lower than that in traditional fuel-based generation. The variable cost of the PV and wind turbine is zero. However, the cost of fuel-based generation consists of both fixed and variable cost. Therefore, after the fixed cost is recovered, the output of these renewable generations can be seen as zero cost, which could lead to reduced electricity sell price. Furthermore, since the electricity is transmitted and consumed locally in distribution network, the transmission network charges are removable. Consequently, customers with cheap generation could make a fortune by selling excessive electricity in the local energy market instead of dumping it to distribution network operators.

- Buyers/Sellers/Speculators/Middlemen:

The customers with energy storage could be both buyers and sellers in the local energy market. Compared with typical buyers in the local energy market, this type of customers has even more flexible demand or extra demand. The purchase behaviour during a specific time period would cause no comfort sacrifice. Compared with typical sellers in the local energy market, the electricity sell time for this type of customers is not limit to generation time. Since energy storage could shift energy to whenever wanted, the customers with energy storage could be speculators in the local energy market who buy electricity at cheap price and sell it when the price increases or the demand increases, especially sell it as back up or urgent demand.

In the local energy market, the trading behaviour of customers with energy storage

is the most unpredictable. The customers are flexible with trading behaviours and could always arbitrage in the market. In this study, the research focus on investigate the optimal trading behaviour of customers with energy storage.

7.4 Optimization model of demand flexibility

In this work, optimization of home area energy management system is used to help an individual customer decide whether to stay in central market or participate local electricity trading. More specifically, similar with the previous chapters, the power transfers between home and grid, between local AC and DC generation, demand and battery are modelled.

The battery and converter operation algorithm is designed to optimize the AC and DC power transfer with minimum electricity cost or maximum electricity revenue from energy markets. The constraints come from the battery and converter devices and power balance.

In reality, the trading behaviour might be decided based on the real time central and local prices and bilateral contract at each time slot. The energy management system could only determine the optimal trading behaviour with maximal user benefit using forecasted central and local energy prices. Therefore, the results generated from the EMS will provide a guide of optimal trading arrangement for customers based on the given prices. More important, the results will also give an indication that what kind of local energy price could encourage customers to take part in local electricity trading.

A. Objective

The objective is to minimize the cost of electricity. For each time period, electricity either flow in or flow out from home. It is not allowed to sell expensive electricity to local market and buy cheap electricity from central/local market at the same time. Therefore:

$$\text{Min} \sum_{t=n}^{t=m} Pr(t)P_{AC}(t)T \quad (7-1)$$

$$Pr(t)P_{AC}(t) = \begin{cases} C(t)P_{Cen}(t) + U(t)P_{Lo-B}(t) & \text{when buy electricity} \\ S(t)P_{Lo-S}(t) & \text{when sell electricity} \end{cases} \quad (7-2)$$

Where, n is the trading start time, m is the trading end time. $Pr(t)$ is the electricity price at time t . $P_{AC}(t)$ is the home and grid transferred power at time t . $C(t), U(t), S(t)$ are central electricity are price, local buy and sell electricity price; $P_{Cen}(t), P_{Lo-B}(t), P_{Lo-S}(t)$ are electricity brought from central market, electricity brought from local market and sold to local market.

The total home and grid transfer power is the sum of original AC demand and converted DC demand. The AC and DC power balance are shown as follows:

$$P_{AC}(t) = P_{AC-load}(t) + P_{conv}(t) \quad (7-3)$$

$$P_{conv}(t) = \begin{cases} \eta_{A/D}P_{DC}(t) & \text{if } P_{DC}(t) > 0 \\ 0 & \text{if } P_{DC}(t) = 0 \\ \eta_{D/A}P_{DC}(t) & \text{if } P_{DC}(t) < 0 \end{cases} \quad (7-4)$$

$$P_{DC}(t) = P_{DC-load}(t) + P_S(t) - P_{PV}(t) \quad (7-5)$$

$$P_S(t) = \begin{cases} \eta_c P_{S-in}(t) & \text{if } P_{S-in}(t) > 0 \\ 0 & \text{if } P_{S-in}(t) = 0 \\ \eta_d P_{S-in}(t) & \text{if } P_{S-in}(t) < 0 \end{cases} \quad (7-6)$$

Where $P_{AC-load}(t)$ is customer's AC load at time t ; $P_{conv}(t)$ is the AC demand converted from DC demand at time t ; $P_{DC}(t)$ is the DC demand at time t ; $\eta_{A/D}, \eta_{D/A}$ are AC-to-DC and DC-to-AC conversion efficiencies, $\eta_{A/D} > 1$ and $\eta_{D/A} < 1$; $P_{DC-load}(t)$ is customer's DC load at time t ; $P_S(t)$ is battery charging/discharging power from and to grid at time t ; Battery is taken as DC load, when the battery charges, $P_S(t) > 0$; when discharges, $P_S(t) < 0$; when battery is idle, $P_S(t) = 0$. $P_{PV}(t)$ is PV output at time t ; $P_{S-in}(t)$ is battery stored power at time t . η_c, η_d are battery charging and discharging efficiencies.

B. Constraints

The constraints of home and grid transferred power, devices and power balance should be satisfied, which are:

- Constraints of home and grid transferred power

The power direction between home and grid are represented by positive and negative signs. The power drawn from grid, either from central market or local market, are represented by positive value. The power selling from home to grid is represented by negative value.

$$P_{cen}(t) \geq 0 \quad (7-7)$$

$$P_{Lo-B}(t) \geq 0 \quad (7-8)$$

$$P_{Lo-S}(t) \leq 0 \quad (7-9)$$

- Constraints of devices

1. Battery charging and discharging rates should be within certain ranges, which are constrained by its physical properties.

$$P_D^{max} \leq P_{S-in}(t) \leq P_C^{max} \quad (7-10)$$

Where P_C^{max} , P_D^{max} are battery maximum charging and discharging rate.

2. The amount of energy stored in the battery is limited:

$$E_{min} \leq E(t) \leq E_{max}, \quad t = 1, 2, \dots, 47 \quad (7-11)$$

$$\begin{cases} E(t) = E(t-1) + \Delta E(t) & t = 1, 2, \dots, 48 \\ \Delta E(t) = P_{S-in}(t)T \end{cases} \quad (7-12)$$

3. The converting power should be within the converter rating power.

$$-R \leq P_{conv}(t) \leq R \quad (7-13)$$

Where R is the converter rating power.

- Constraints of power balance

The battery is operated for trading time. It is assumed that when trading ends, the battery will have the states when trading starts. Therefore, the sum of charging and discharging power of trading period is assumed to be zero:

$$\sum_{t=n}^m P_{S-in}(t) = 0 \quad (7-14)$$

7.5 Problem formulation

In the proposed optimization model, there are multiple power sources from grid and home, such as central market, local market, distributed generation, storage, and multiple power consumers, such as local market, storage, AC and DC loads. The optimization process is to determine the best power sources for the power consumers with lowest cost and best time to buy and sell electricity with maximum revenue.

The original optimization problem is formulated by a Mixed Integer Linear Programming (MILP) model. In detail, firstly, the whole system is divided to four hierarchical components: battery, local DC network, local AC network and main grid. Therefore, the power flow between four components has three levels, i.e. local AC network-grid level, local AC-DC network level and battery-DC network level shown as figure 7-4. The power balance within each component can be represented by different functions. The bi-direction power flow in the three levels, i.e. $P_S(t)$, $P_{conv}(t)$ and $P_{AC}(t)$, are split and replaced by single direction power flow. Specifically, $P_S(t)$ is replaced by two variables: charging power $P_C(t)$ and discharging power $P_D(t)$; $P_{conv}(t)$ is replaced by two variables: AC-to-DC power $P_{AC-DC}(t)$ and DC-to-AC power $P_{DC-AC}(t)$; $P_{AC}(t)$ is replaced by the three variables with different electricity source and direction: $P_{Cen}(t)$, $P_{Lo-B}(t)$ and $P_{Lo-S}(t)$. Binary numbers, as coefficients, are used to distinguish power flow for different directions as shown in table 7-1. The final decisions of power sources and power flow at each time slot are determined by optimization process.

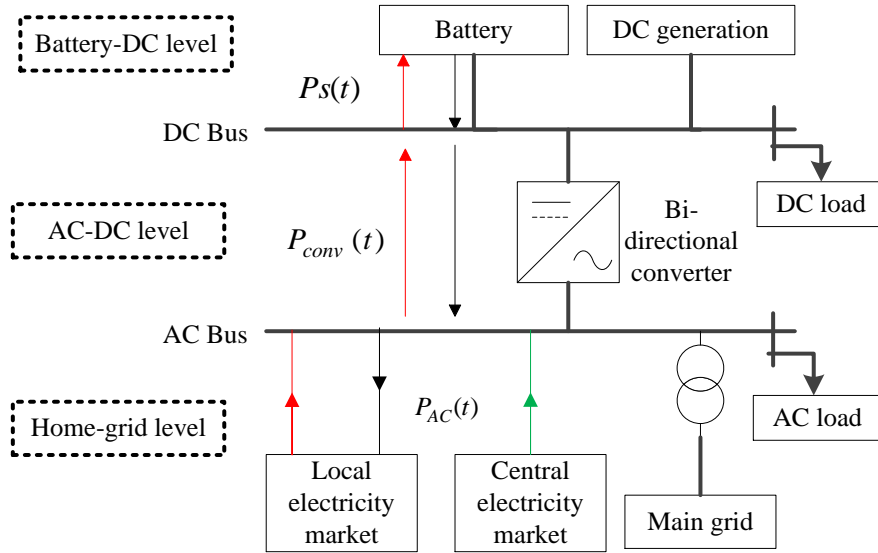


Figure 7-4 Overview structure of the EMS system

Table 7-1 Scenarios with different binary coefficients

Home-grid level	$P_{Cen}(t)$ $P_{Lo-B}(t)$	$P_{Lo-S}(t)$	Description
Binary coefficient	0	1	Sell electricity to local market
Binary coefficient	1	0	Buy electricity from central/local market
AC-DC level	$P_{AC-DC}(t)$	$P_{DC-AC}(t)$	Description
Binary coefficient	0	1	Local DC network support local AC network
Binary coefficient	1	0	Local AC network support local DC network
Battery-DC level	$P_C(t)$	$P_D(t)$	Description
Binary coefficient	0	1	Battery discharge
Binary coefficient	1	0	Battery charge

The new optimization model is shown as:

A. Objective

The objective is to minimize the cost of electricity (maximize the electricity sale

revenue).

$$\text{Min } \sum_{t=n}^m C(t)P_{Cen}(t)T + U(t)P_{Lo-B}(t)T + S(t)P_{Lo-S}(t)T \quad (7-15)$$

The power balance of system components can be represented by three functions.

1. Power balance on local AC network:

$$P_{Cen}(t) + P_{Lo-B}(t) + P_{DC-AC}(t) \times \eta_{D/A}^* = P_{AC-load}(t) + P_{AC-DC}(t) + (-P_{Lo-S}(t)) \quad (7-16)$$

2. Power balance on local DC network:

$$P_{PV}(t) + P_{AC-DC}(t) \times \eta_{A/D}^* + P_D(t) \times \eta_D^* = P_{DC-load}(t) + P_C(t) + P_{DC-AC}(t) \quad (7-17)$$

3. Power balance in battery:

$$P_C(t) \times \eta_C^* - P_D(t) = P_{S-in}(t) \quad (7-18)$$

B. Constraints

The constraints of home and grid transferred power, devices and power balance should be satisfied. To distinguish the bi-direction power flow between four system components, battery, local DC network, local AC network and main grid, binary numbers, x, y and z are introduced.

1. Constraints on local AC network-grid level

For each time period, electricity either flow in or flow out from home. It is not allowed to sell expensive electricity to local market and buy cheap electricity from central/local market at the same time. Two extremely large numbers, M and N , and the binary number are used to guarantee only one of the situations happens.

$$0 \leq P_{Cen}(t) \leq (1 - x) \times M \quad (7-19)$$

$$0 \leq P_{Lo-B}(t) \leq (1 - x) \times M \quad (7-20)$$

$$x \times N \leq P_{Lo-S}(t) \leq 0 \quad (7-21)$$

$$0 \leq x \leq 1 \quad x = 0 \text{ or } 1 \quad (7-22)$$

Where M is a large positive number and N is a large negative number.

2. Constraints on local AC –DC network level

$$0 \leq P_{AC-DC}(t) \leq y \times R \quad (7-23)$$

$$0 \leq P_{DC-AC}(t) \leq (1 - y) \times R \quad (7-24)$$

$$0 \leq y \leq 1 \quad y = 0 \text{ or } 1 \quad (7-25)$$

3. Constraints on battery-DC network level

$$0 \leq P_C(t) \leq z \times P_C^{max} \quad (7-26)$$

$$0 \leq P_D(t) \leq (1 - z) \times (-P_D^{max}) \quad (7-27)$$

$$0 \leq z \leq 1 \quad z = 0 \text{ or } 1 \quad (7-28)$$

4. Constraints of battery stored energy

$$E_{min} \leq E(t) \leq E_{max}, \quad t = 1, 2, \dots, 47 \quad (7-29)$$

$$\begin{cases} E(t) = E(t-1) + \Delta E(t) & t = 1, 2, \dots, 48 \\ \Delta E(t) = P_{S-in}(t)T \end{cases} \quad (7-30)$$

$$\sum_{t=1}^{48} P_{S-in}(t) = 0 \quad (7-31)$$

7.6 Demonstration

The battery and converters control strategy and benefits of local electricity trading are shown and discussed in this section. The proposed optimal energy management and trading method is validated in a domestic home and a primary school in Bristol, UK. Both customers have AC and DC demand and distributed energy resources, i.e. PV and

storage. The whole day trading is simulated with assumed central and local energy prices. Three local energy prices and one central electricity price are tested to illustrate introduced different profitability.

The relationship between central and local electricity prices determines the profitability of local electricity trading. In this study, different relationships between central and local prices are demonstrated to discuss the differences in customer trading behaviours and trading benefits. The used central market price is derived from the wholesale energy price of Great Britain (GB) [106]. The used central TOU price is shown in figure 7-5.

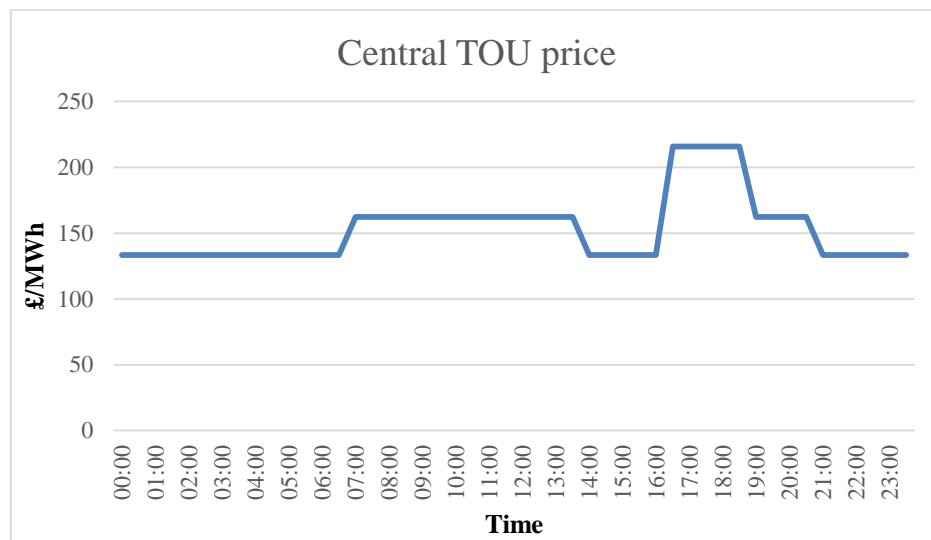


Figure 7-5 Central TOU price

As shown in figure 7-6, three different local prices are assumed to demonstrate the local market trading opportunities and benefits. In the case study, the three local market prices are simulated as electricity buy and sell price respectively. The price is agreed between different customers for each trading time period.

It should be mentioned that the local market prices used in this study are referenced from existing electricity price, which are not limited to developed local energy prices. The cited prices are used to demonstrate the optimal energy management system for electricity trading and different trading opportunities and benefits. More sophisticated local electricity prices could be developed and applied to this energy management system in the future.

In the figure below, price 1 represents a local electricity price that is lower than the central electricity price for all the time [106]. The price is scaled from wholesale energy price. The tariff can be seen as “wind tariff” since the distributed wind turbine could generate electricity all day. The tariff is between £60-£100/MWh. Price 2 is the “Sunshine Tariff” derived from project “Sunshine Tariff” [158]. During PV output time, between 10:00-16:00, the tariff is quite low as £50/MWh. However, during the rest of the day, the tariff is as high as £180/MWh, which is even higher than the central electricity price. In this study, it aims to encourage customers to buy cheap PV output from local energy market or to sell their own excessive PV energy to the local energy market. Price 3 is derived from Price 2. Compared with Price 2, the Price 3 increases the PV output price and reduces the normal price. Price 2 and Price 3 are highly possible prices in the local energy market offered by two different customers both with PV generations.



Figure 7-6 Local market prices

The load profiles of different customers are significantly different. Therefore, the control strategy and electricity trading flexibility are different depending on different customer behaviours. This study demonstrates that school and domestic customers have different demand and trading flexibilities. As shown in figure 7-7, the PV output peak is at afternoon whilst the peak load of domestic customer is at evening, which leads to great amount of available energy for shifting or sale. However, as shown in figure 7-8, the peak PV output and peak load of school are nearly overlapped, both at daytime. The

available trading energy for school could be limited depending on the market prices.

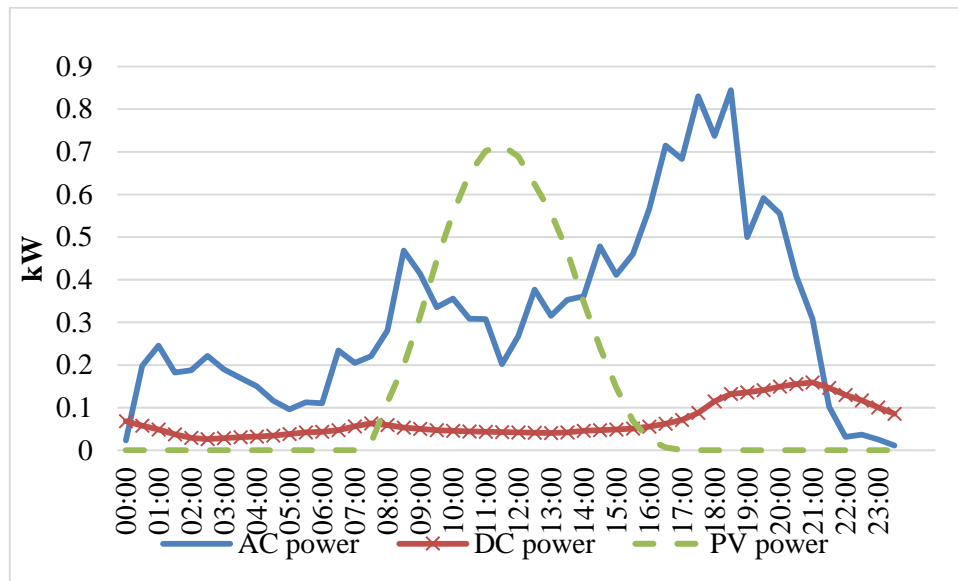


Figure 7-7 Domestic customer demand and PV output

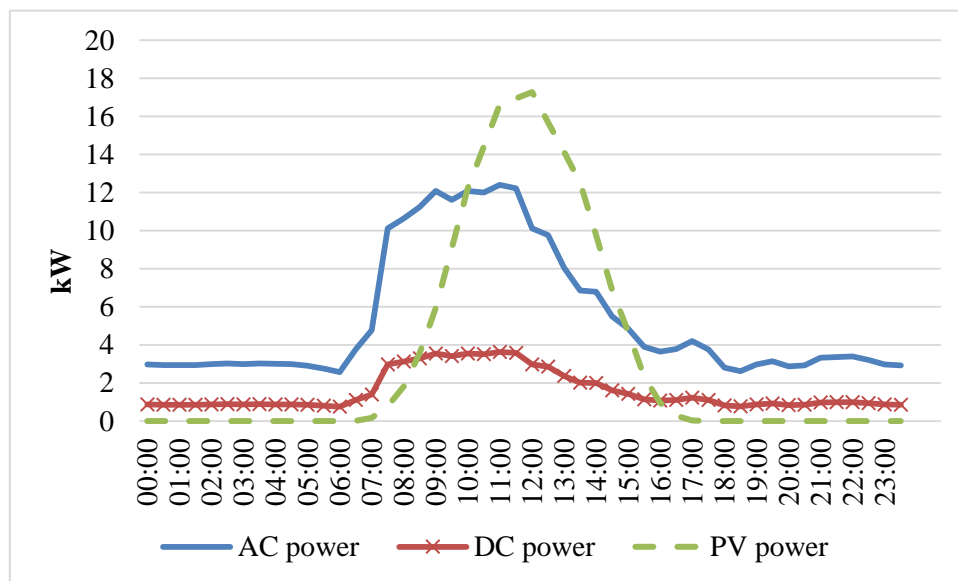


Figure 7-8 School customer demand and PV output

The used battery, converter and PV parameters in domestic house and school are listed in the table 7-2.

Table 7-2 Devices parameters

Parameters	Domestic	School
Battery capacity	4.8 kWh	19.2 kWh
Battery charging current limit	40 A	180 A
Battery discharging current limit	40 A	180 A
Battery Max/Min SOC	0.9/0.3	0.9/0.3
Battery charge/discharge efficiency	99%	99%
Converter rating	10 kW	40 kW
Converter efficiency	90%	90%
PV capacity	2 kWp	30 kWp

The results are shown and compared with different local prices and customer types.

7.6.1 Benefit analysis

Six cases as shown in table 7-3 are considered to compare the energy cost, trading opportunities and control strategies. Base case is the traditional market environment, in which, there is only central energy market and customers are not allowed to sell energy to the energy market. Two types of price match scenarios, discriminatory prices [149] and uniform clear price, are considered in the case study. Cases 1 to case 4 are different combinations of local buy and sell prices. Since there are different local buy and sell prices, the cases can be seemed as the bids and asks are matched with discriminatory prices [149] or as agreed bilateral contracts between customers. Case 5 provides same local buy and sell prices, which indicates a uniform clear price in local energy market. It should be mentioned that the results in the following section give the most profitable DSR trading behaviours. However, whether the DSR trading is feasible and reasonable is discussed in detail as the summary.

Table 7-3 Cases with different prices

Cases	Local buy price	Local sell price
Base case	0	0
Case 1	Price 2	Price 1
Case 2	Price 1	Price 2
Case 3	Price 3	Price 2
Case 4	Price 2	Price 3
Case 5	Price 2	Price 2

The minimum energy costs of the six cases for the customers are shown in table 7-4. The cost includes the DSR trading cost/benefit and the bill saving from self-consumed PV output. The domestic customer could save significantly more than that of school

customer. All the cases could bring average 30% cost saving to the domestic customer and 5% cost saving to the school customer. For both customers, when local buy and sell prices are different, the energy cost savings follows the relationship that: Case 2 > Case 1 > Case 4 > Case 3. Case 2 is the only case that will bring negative cost, i.e. revenue to the customers. Case 5, which uses market clear prices, could save 30.6% cost saving for domestic customer and 4.9% for school.

Table 7-4 Energy cost in different cases

Cases	Domestic (£/day)	School (£/day)
Base case	0.919	10.704
Case 1	0.627 (-31.8%)	9.670 (-9.7%)
Case 2	-0.03 (-103.3%)	5.245 (-51%)
Case 3	0.696 (-24.3%)	10.301 (-3.8%)
Case 4	0.659 (-28.3)	9.906 (-7.5%)
Case 5	0.638 (-30.6%)	10.181 (-4.9%)

7.6.2 Trading behaviour analysis for different local prices

Domestic customer scenarios are discussed in detail in this section to compare the trading opportunities and optimal trading behaviours with different local prices. In the base case, all the energy is purchased from central energy market as shown in figure 7-9 and figure 7-10. During the peak price time, i.e. between 16:30-19:00, the purchased energy is reduced since battery is discharged to support local AC network. This trading arrangement will cost customer £0.919/day for buying electricity.



Figure 7-9 Trading prices in base case

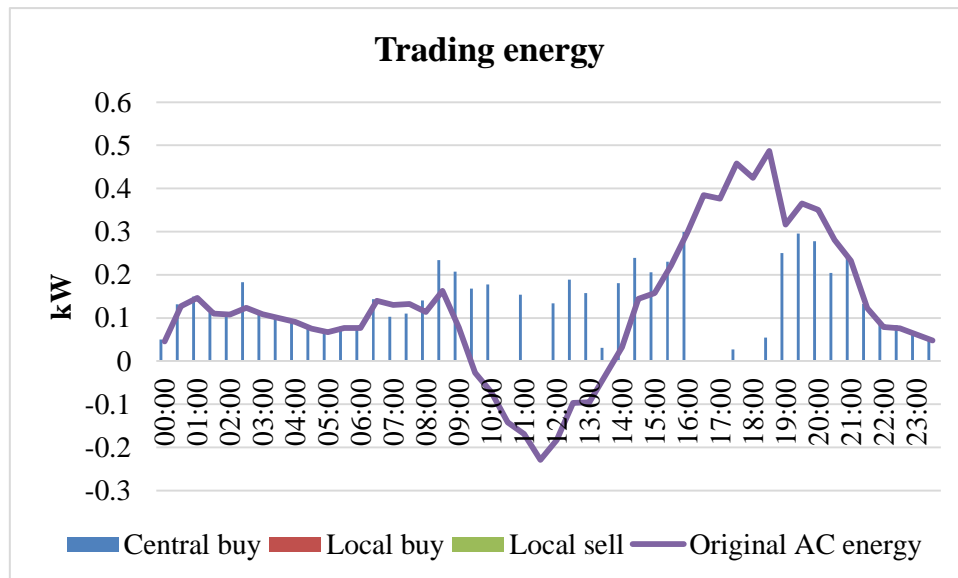


Figure 7-10 Trading energy in base case

Case 2 brings largest benefit to the customers, i.e. introduces £0.03 revenue in electricity trading. Case 2 simulates the situation that this customer has found bargains in the local energy market that the electricity buy price is 45% lower than the central electricity price for 24 hours and could offer a “sunshine tariff” to the local energy market.

The trading prices and optimal trading behaviour are shown in figure 7-11 and figure 7-12. The bar charts show the trading energy and the line chart indicates the original required AC energy at each time slot. It is shown that the customer only trades

electricity in local energy market. The customer buys all the needed electricity from local energy market. During early morning and evening after 16:00, when local market bid price is low, the customer arbitrages in the local energy market, i.e. buys cheap electricity to charge battery and to sell it at a higher price to another customer in the local energy market. During the PV output period, 10:00-16:00, instead of selling the excessive PV output to another customer, the optimal solution is that the battery of this customer absorbs the PV energy for later demand peak and high price sale purposes. Additionally, more is bought electricity from local energy market during this time period for later usage and sale.



Figure 7-11 Trading prices in case 2

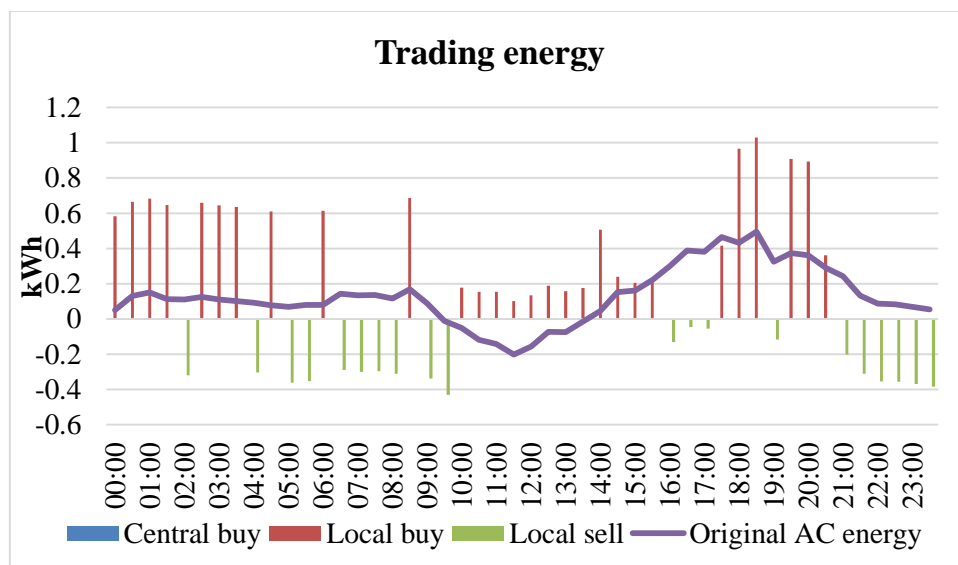


Figure 7-12 Trading energy in case 2

Case 1 is the second profitable case for customers, reducing 31.8% energy cost. In case 1, this customer have accepted a “sunshine tariff” from another customer and offered a “wind tariff”.

The trading prices and optimal trading behaviour are shown in figure 7-13 and 7-14. The customer buys electricity in lower prices between central and local market, and sells electricity during PV output time when a higher price offer can be accepted. During early morning between 00:00-10:00, when central market price is low, the customer buys electricity from central energy market. Then the customer arbitrage in the local energy market when there is free PV output, cheap local market electricity and high electricity sell price. It is shown that customer buys electricity three times of the needed from local market between 13:00-16:00. The bought cheap excessive electricity is stored in the battery and used during peak demand time, 16:00-18:30, when electricity price is high as well. The bought electricity during 19:00-21:00 is less than the needed as shown in the bar and line in the figure, which indicates the battery is supporting the local demand during the period.

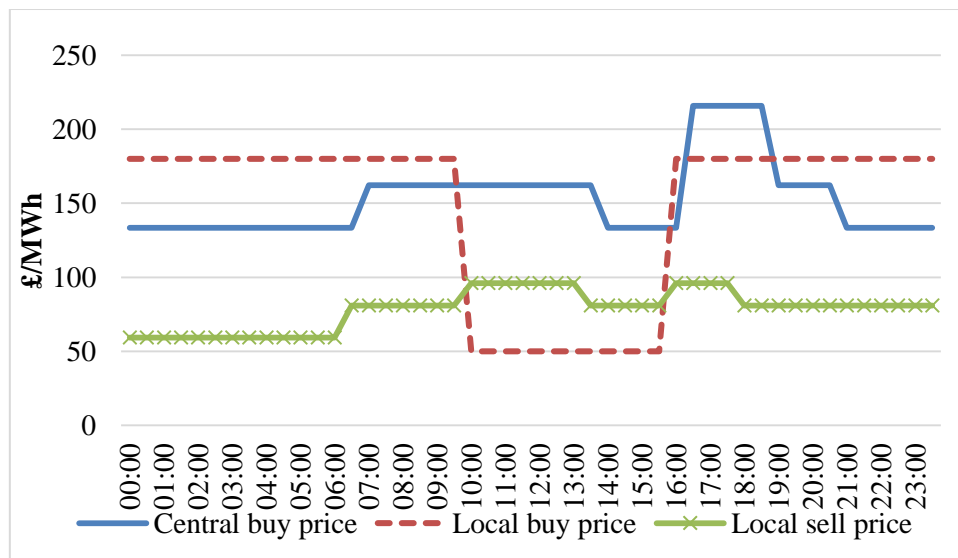


Figure 7-13 Trading prices in case 1

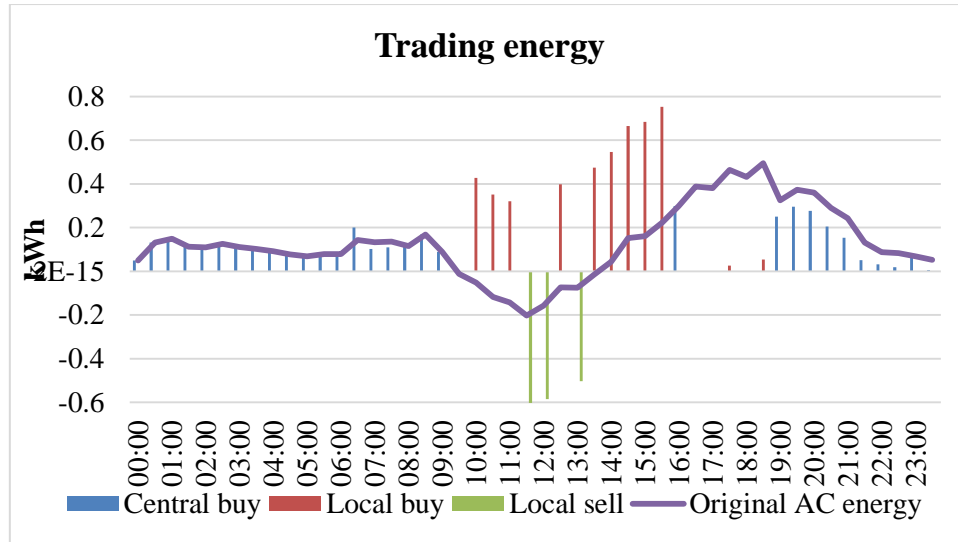


Figure 7-14 Trading energy in case 1

As shown in the results, case 4 introduces a slightly reduced benefit for customers compared with case 1. In case 4, two “sunshine price” are used in local market trading as shown in figure 7-15. It can be concluded from figure 7-13 and figure 7-15, there are similar relationship of central price, local buy and sell price between case 1 and case 4. In detail, 1) between 00:00-10:00, local electricity buy price is higher than central price; 2) between 10:00-16:00, local sell price is higher than local buy price; 3) between 16:00-18:30, central price is higher than local buy price and local sell price. Therefore, the optimal trading behaviour of customer in case 4 is similar with that in case 1 as shown in figure 7-16.

Compared with case 1, the differences of trading behaviour in case 4 is the customer arbitrages between central and local market since local sell price is higher than central price during 00:00-10:00 and during 18:30-00:00.



Figure 7-15 Trading prices in case 4

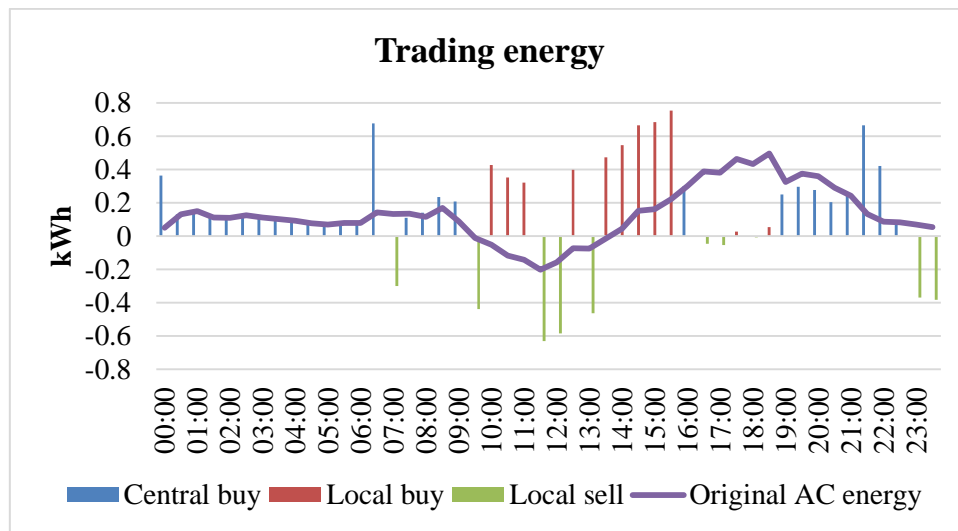


Figure 7-16 Trading energy in case 4

Case 3 is the least profitable case for customers, reducing 24.3% energy cost. In this case, two “sunshine price” are used in local market trading for simulation. However, the local buy and sell prices are exchanged compared with that in case 4. This customer have accepted a “sunshine tariff” from another customer and offered a local electricity price to the local market that is higher in non-PV output time and lower in PV output time.

The trading prices and optimal trading behaviour are shown in figure 7-17 and figure 7-18. The customer buys electricity in lower prices between central and local market, and sells electricity during PV output time when a higher price offer can be accepted. Before 10:00 and after 18:30, when local market sell price is higher, the customer

arbitrages between central and local energy market, i.e. buys cheap electricity to charge battery and to sell it at a higher price to another customer in the local energy market. Additionally, the customer buys electricity from local market during 17:30-18:30, when demand is high and central price is high, for arbitrage in the late evening. During the PV output period, 10:00-16:00, instead of selling the excessive PV output to another customer, the optimal solution is that the battery of this customer absorbs the PV energy for later demand peak and high price sale purposes.

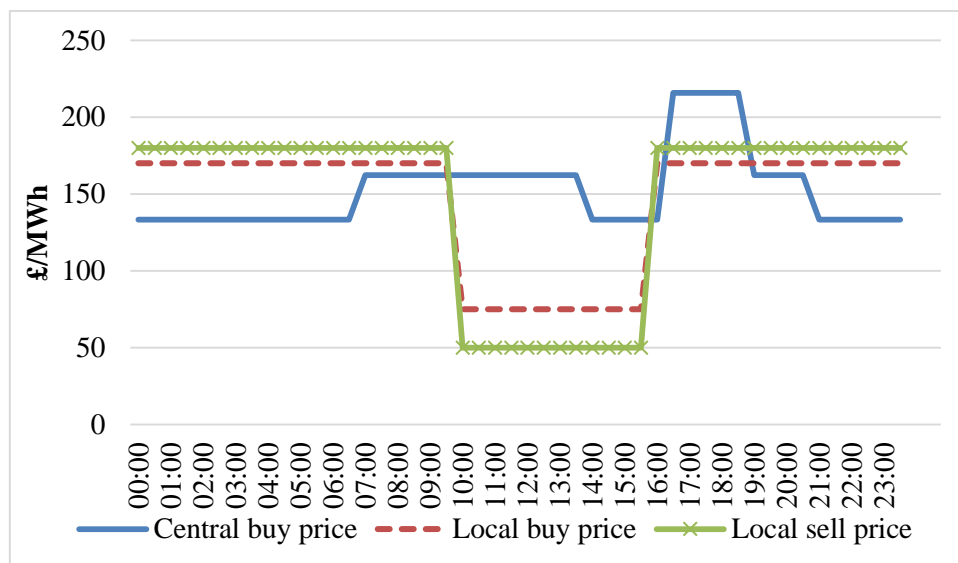


Figure 7-17 Trading prices in case 3

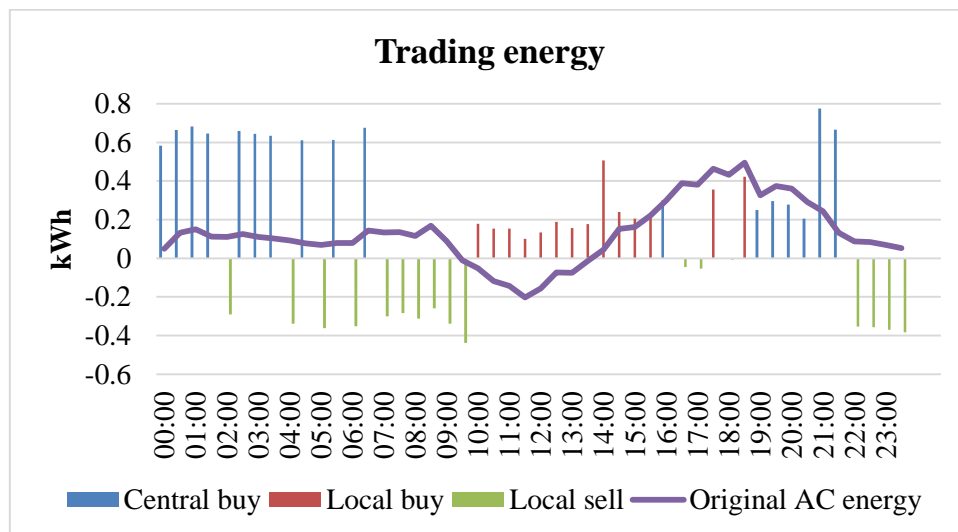


Figure 7-18 Trading energy in case 3

Case 5 reduces around 30% energy cost. In this case, a unique clear price, “sunshine tariff” is used in local market trading.

The trading prices and optimal trading behaviour are shown in figure 7-19 and figure

7-20. It is shown that the trading behaviour in case 5 is the same with that in case 3. The different trading amount and trading prices in case 5 leads to different benefit compared with that in case 3.



Figure 7-19 Trading prices in case 5

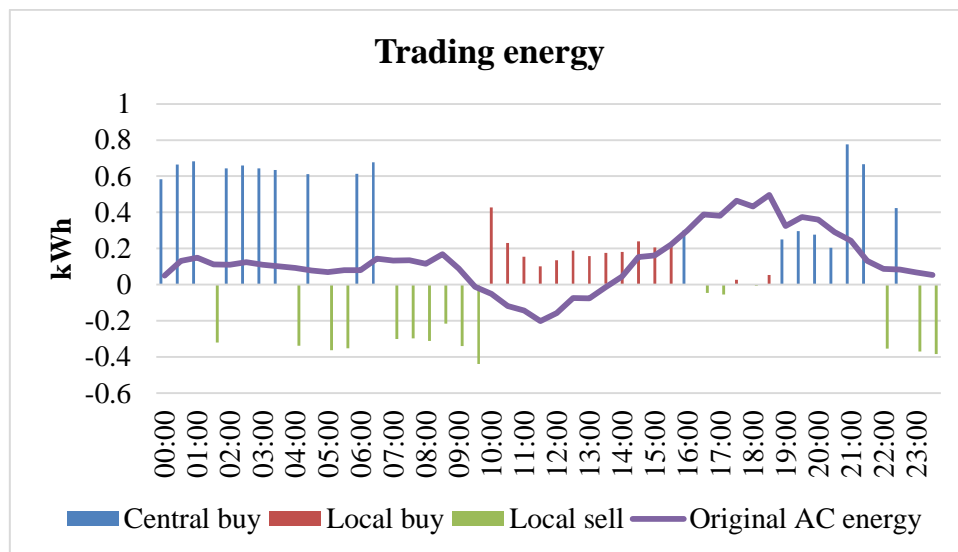


Figure 7-20 Trading energy in case 5

The reason of the different profitability among cases can be summarized in table 7-5:

Table 7-5 Traded energy buying and selling prices

Reasons of benefit		Power trading			Demand shifting	
Profitability rank	Case No.	Unit purchase price	Unit selling price	Unit profit (£/kWh)	Shifted peak demand	Demand shifting profit

		(£/kWh)	(£/kWh)		purchase price (£/kWh)	(£/kWh)
1	2	59.2-80.79 (from local)	180	120.8-99.21	80.79-96.11 (from local)	119.63-134.95
2	1	50 (from local)	96.11	46.11	50 (from local)	165.74
3	5	133.34 (from central)	180	46.66	50 (from local)	165.74
4	4	50 (from local)	75	25	50 (from local)	165.74
5	3	133.34 (from central)	180	46.66	75 (from local)	140.74

1. The increased difference between sell and buy price will lead to increased cost saving. Additionally, the increased demand shifting profit will lead to the larger cost saving. Since the aim of home energy optimization system is to maximize the benefit of the specific user, the optimal solution is always buying cheap electricity and only selling it when electricity sell price is higher than buying price.
2. The customers with battery are not suitable to offer a “sunshine tariff” even they have PV in their homes. As shown in case 2, case 3 and case 5, this type of customers will not implement the trading arrangement to sell cheap electricity as they supposed to when there is excessive PV output. These customers will not sell electricity during low price period in “sunshine tariff” unless they could buy electricity at an even lower price as shown in case 4. On the contrary, the customers with battery are suitable to accept the “sunshine tariff” from PV-only holder and to use battery to arbitrage by shifting the power and selling the electricity in another time.
3. If the “wind tariff” is neither the highest nor the lowest price in the local energy market, it is suitable for customers with battery. The customers with battery

could take full advantage of long-time moderate and stable price to flexibly arbitrage in the local energy market, i.e. buy from and sell to another customer whenever they have spare battery capacity or excessive electricity. The moderate “wind tariff” could act as insurances to guarantee the benefit of customers with battery.

4. Different from scenarios of customers with only distributed generation, the customers with battery have more trading flexibility and could freely choose the time and amount to trading in the markets. Therefore, in the local energy market, the customer with battery could play as a middleman, who buys electricity at low demand period with cheapest price from a PV-only holder or from a wind turbine only holder and sells it with increased price when demand is increased.

7.6.3 Result discussion for different customer types

The control strategy and electricity trading flexibility of different customer types with different load profiles are discussed in this section. The case 5 and case 2 are taken as examples to illustrate the control strategy and trading behaviours.

Both school and domestic customers receive the average cost saving in case 5 compared with other cases. However, the control strategies and trading flexibility are significantly different between the two customers because of the different local profiles as shown in figure 7-21 and figure 7-22. The battery charges/discharges more cycles and the AC-DC power exchange is more frequent in domestic homes for maximum benefits. Accordingly, the energy trading is more active in domestic home. In domestic home, the battery charges and discharges frequently to exchange AC-DC power in the early morning. However, the school battery stays below 35% SOC. It turns out that the battery helps domestic customer to sell electricity in local energy market while school customer only buys needed energy from central energy market, where the electricity is cheap. Between 9:00-16:00, the battery in domestic home charges to 90% SOC to absorb all the PV output. At the same time, domestic customer buys cheap electricity from local energy market for its own AC demand. While, the battery in school charges a part of PV output and the left PV output is converted to AC power during the day to support AC demand as well as sell to local energy market as shown in figure 7-23 and figure 7-24. Between 16:00-18:30, when electricity is expensive from both central and

local energy market, batteries are discharged to 30%-40% of SOC to mainly support local demand. At late night, when demand is low, the battery in domestic home charges and discharges 25% SOC for AC-DC power exchange and local energy trading.

It can be concluded that with the help of battery, the domestic customer, whose demand peak time is different from PV output peak time, has shown more trading flexibility and feasibility than the school customer.

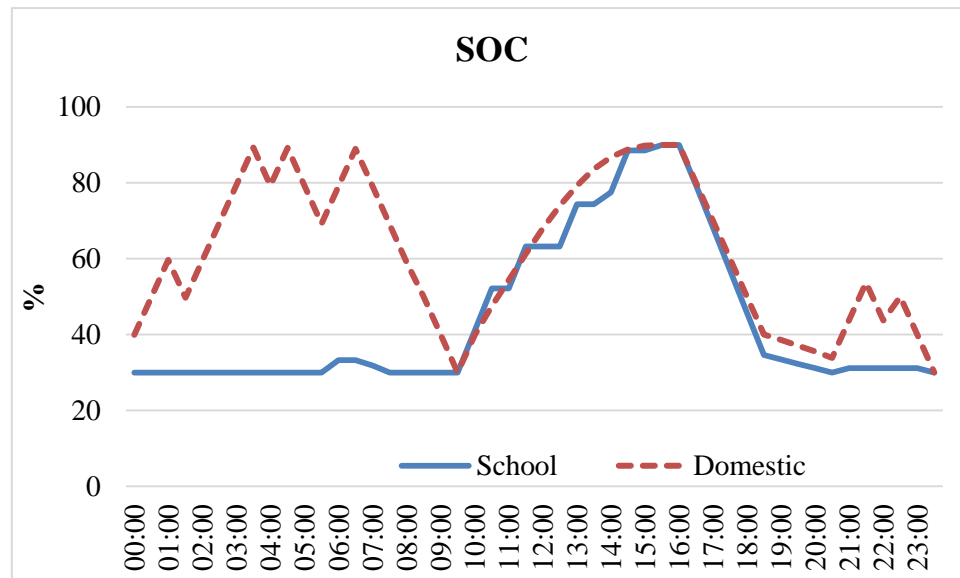


Figure 7-21 Battery SOC comparison in case 5

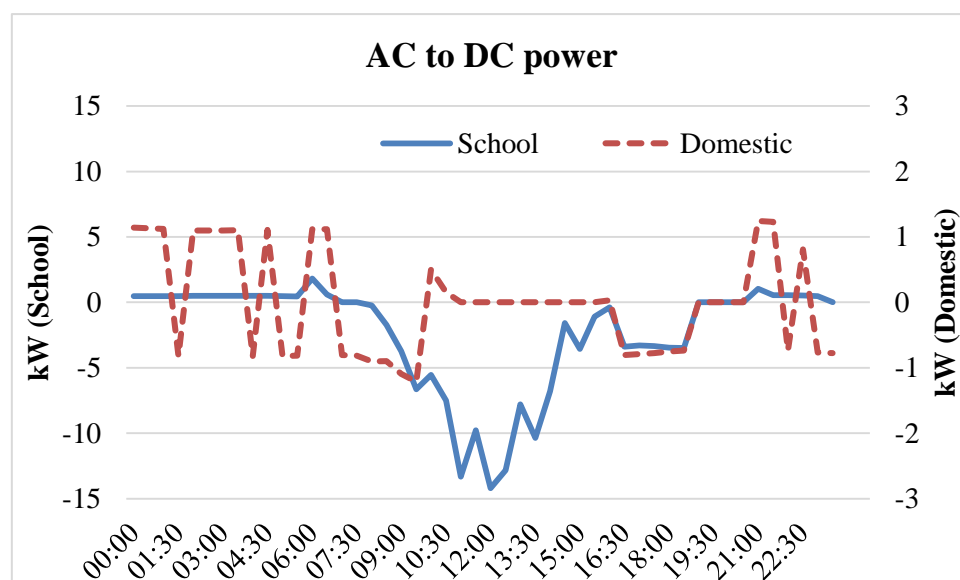


Figure 7-22 AC-DC power exchange comparison in case 5

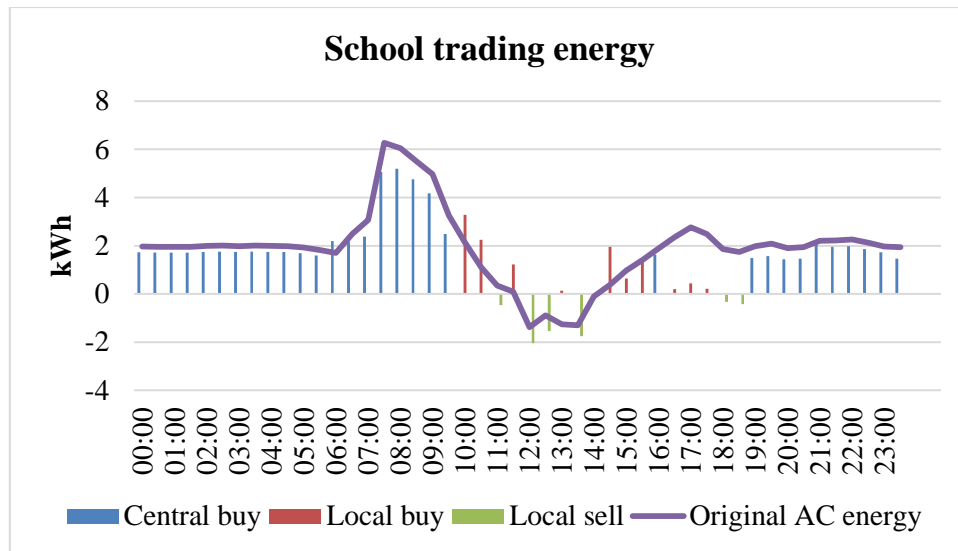


Figure 7-23 Trading energy of school in case 5

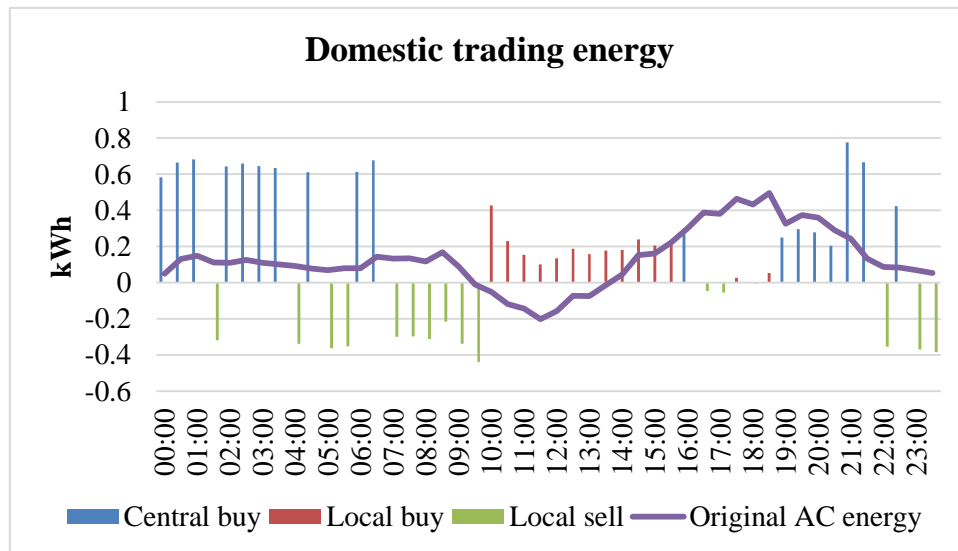


Figure 7-24 Trading energy of domestic home in case 5

In case 2, both customers receive dramatic energy cost savings or even revenue in energy trading. It is explained in the last section that the local price setting in case 2 provides great opportunities for customers to arbitrage in the local energy market. As shown in the last section, the domestic customer keeps buying and selling electricity in the local energy market and receives £0.03 revenue.

The battery and converter control strategies comparisons of the two customers are shown in figure 7-25 and figure 7-26. The school customer charges two cycles and the domestic customer charges two and half cycles during the day. Accordingly, the AC-DC power transfer between 0:00-9:00 and 16:00-21:00 is frequent since the battery

charges to store the bought cheap energy, and discharges to support AC demand and sell stored electricity. Similar with case 5, between 9:00-16:00, the battery in domestic home charges to absorb all the PV output, whilst, the battery in school charges a part of PV output and the left PV output is converted to AC power during the day to support AC demand as well as sell to local energy market.

However, the trading behaviours between the two customers are different. It is shown in the figure 7-27 and figure 7-28 that the sold electricity in domestic home is significantly larger than that in school. Majority of the discharged electricity in school's battery is to reduce the AC demand of school itself instead of sale.

Therefore, the domestic customer, whose demand is lower than that of school, has more trading flexibility and feasibility than the school customer. It can be deducted that the customer with lower demand or larger battery would have more trading flexibility and feasibility.

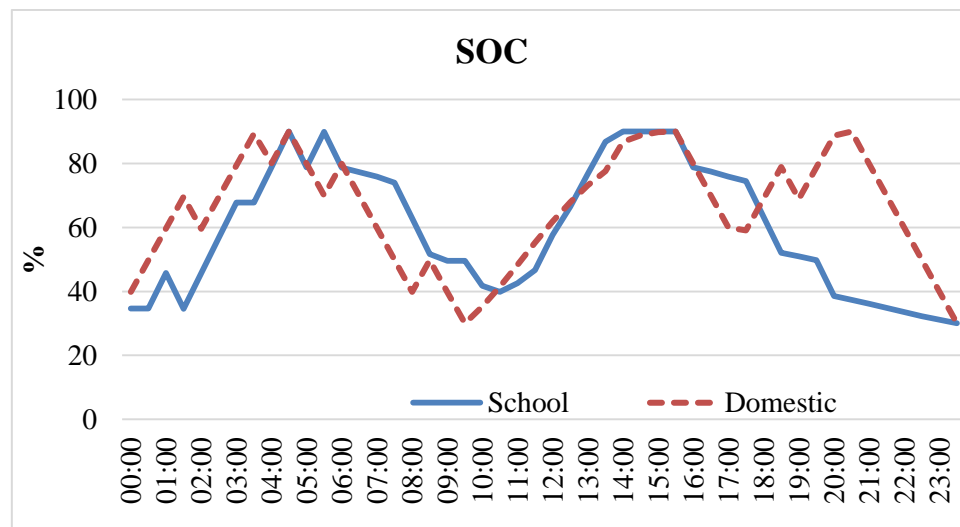


Figure 7-25 Battery SOC's comparison in case 2

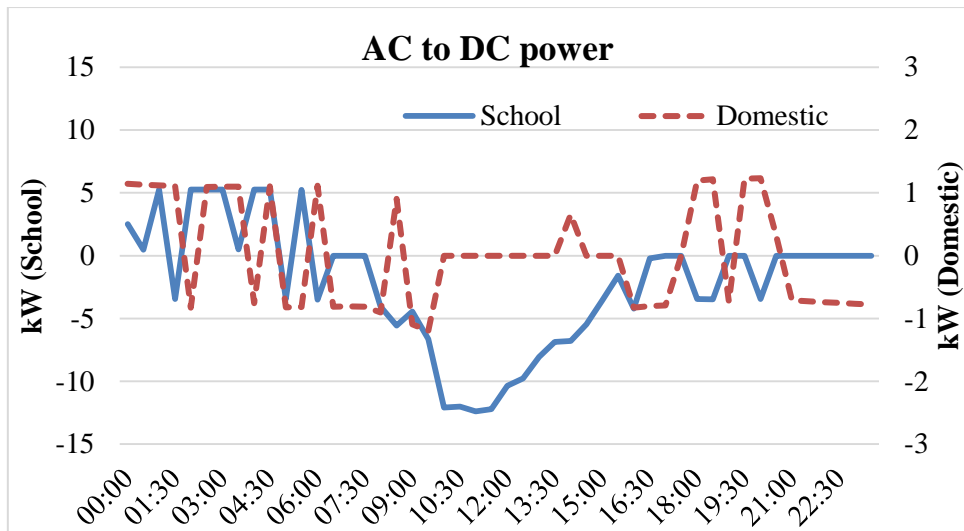


Figure 7-26 AC-DC power exchange comparison in case 2

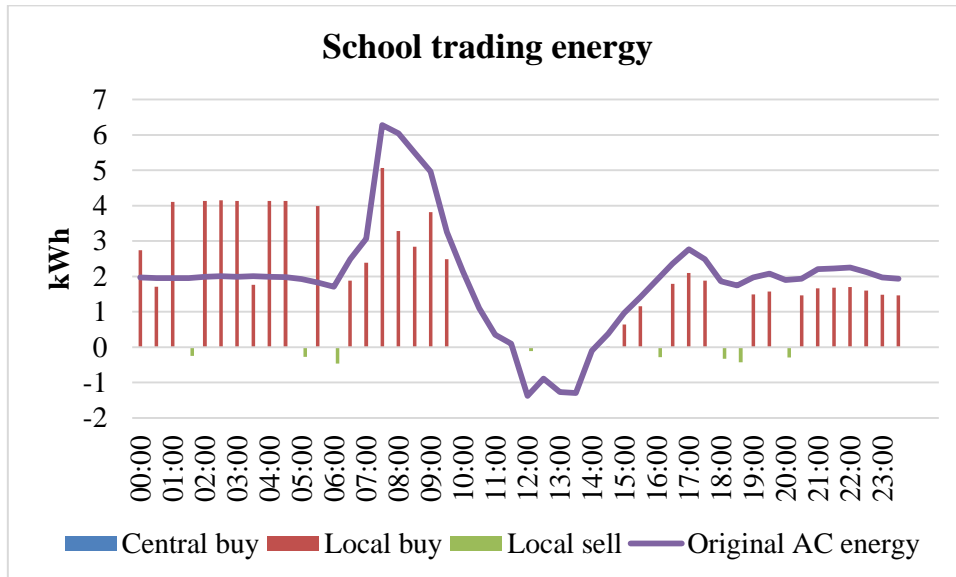


Figure 7-27 Trading energy of school in case 2

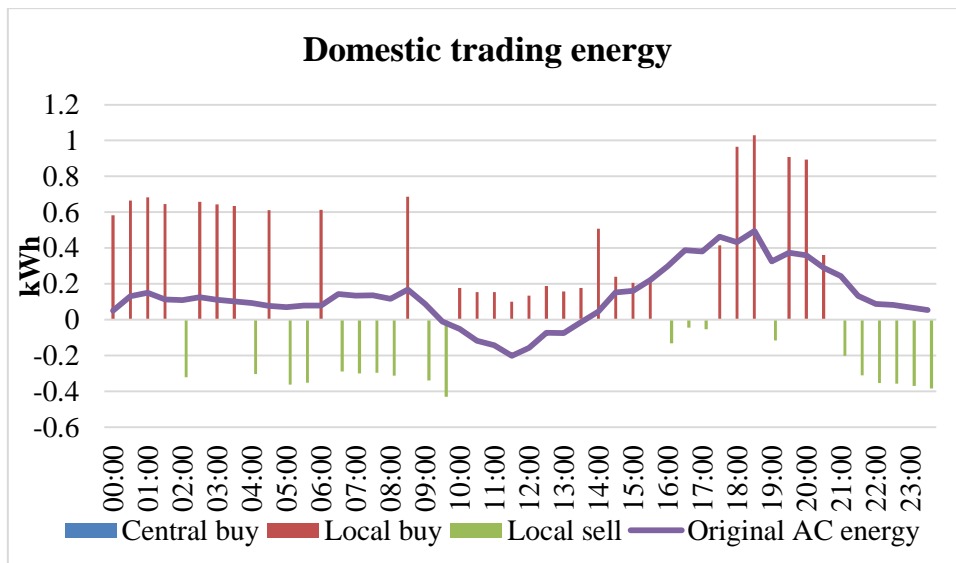


Figure 7-28 Trading energy of domestic home in case 2

7.7 Conclusions

Based on the core DSR optimization tool developed in this research, this chapter of the thesis has investigated DSR benefits in a local energy market environment. Also, key difference between typical domestic and SME (school in this work) DSR activities have been compared. Key findings of derived from this chapter include:

In an environment of local energy markets, customers are able to purchase from electricity from either central or local markets, and to sell their respective surplus to nearby neighbours. From the perspective of customer profitability, the margin between the actual purchase cost and corresponding selling price has a substantial impact on the eventual profitability.

The customers with battery are not suitable to offer a “sunshine tariff” even they have PV in their homes. These customers will not sell electricity during low price period in “sunshine tariff” unless they could buy electricity at an even lower price as. On the contrary, the customers with battery are suitable to accept the “sunshine tariff” from PV-only holder and to use battery to arbitrage by shifting the power and selling the electricity in another time.

If the “wind tariff” is neither the highest nor the lowest price in the local energy market, it is suitable for customers with battery. The customers with battery could take full advantage of long-time moderate and stable price to flexibly arbitrage in the local energy market, i.e. buy from and sell to another customer whenever they have spare battery capacity or excessive electricity. The moderate “wind tariff” could act as insurances to guarantee the benefit of customers with battery.

Different from scenarios of customers with only distributed generation, the customers with battery have more trading flexibility and could freely choose the time and amount to trading in the markets. Therefore, in the local energy market, the customer with battery could play as a middleman, who buys electricity at low demand period with cheapest price from a PV-only holder or from a wind turbine only holder and sells it with increased price when demand is increased.

Compared with SME DSR activities, domestic customers tend to be more suitable

for participating in a local energy market environment. For one thing, the domestic customer, whose demand peak time is different from PV output peak time, has shown more trading flexibility and feasibility than the school customer. At the same time, the domestic customer, whose demand is lower than that of school, has more trading flexibility and feasibility than the school customer.

Chapter 8. **Conclusions and future work**

8.1 Conclusion

Currently, there is limited insight into the DSR strategies and contributions on future downstream markets introduced for the industry to move from DNO to DSO, where a new industry structure and architecture would allow regional energy markets to be developed for small and medium energy customers to actively participate in managing stresses and uncertainty. At present, the majority of the existing downstream network infrastructures and appliances have no capabilities to be managed and controlled for DSR.

However, the increasing number of LCTs, including renewable generations, energy storage and smart metering, integrated in downstream network bring new opportunities as well as challenges in DSR. On one hand, the LCTs offer more demand flexibility, e.g. distributed generations are capable of reducing demand; energy storage and EVs could play more important roles in demand shifting. On the other hand, more intelligent control systems are required for effective DSR for end users and power system. A range of multi-value DSR optimization models are developed to contribute to three key areas:

- 1) Solving complex power flow brought by LCTs to maximise customer DSR benefits: With increased household energy components, especially increasing number of LCTs, in the DSR system, traditional DSR control strategies are either complex to solve or inaccurate to represent the system efficiency. For a simplified but accurate way to optimize the power flow within the low carbon homes, new problem formulations, i.e. piecewise function formulations for optimal DSR model are proposed for both intelligent energy storage control and hybrid AC/DC system control.
- 2) Multi functional DSR benefits: Traditional DSR control strategy is designed for either minimum customer electricity cost or minimum peak-to-average ratio of the network demand. With the development of smart metering and remote control technologies, the benefits for both customers and network operators could be achieved. A new DSR optimization model for multi-functional EMS is designed to maximize the benefits for both and to simulate the DSR performance in peak demand reduction, network investment deferral and energy bill saving. Both the

multi-functional EMS simulation results and practical trial results are demonstrated and discussed. Based on the practical trial results, a novel probability based quantification method is proposed to quantify the minimum required DSR penetration for network demand reduction taking the consideration of demand uncertainty. The proposed method could directly help network operators to estimate the DSR impact on the network.

- 3) Maximising DSR benefit in new energy market arrangements: The increasing number of LCTs and distributed energy resources (DER) offer customers with the capability to access and impact the energy market. Therefore, to facilitate the customer to take part in the energy markets, a new MILP based optimization model for optimal DSR management within central and local energy market is proposed. The optimal results are determined by different bid and ask price signals in central and local energy markets. Through the developed optimal trading opportunities finder, the most feasible and profitable DSR trading behaviours and trading price preference for different customers are investigated.

In summary, this work improves the DSR modelling and optimization via 1) proposing a novel piecewise function formulation that simplifies the problem solving process and introduces more accurate conversion efficiency formulation when optimising energy saving from DSR in shifting energy over time; 2) integrating network benefit into DSR optimization model, and 3) developing optimal DSR management model in multiple market environment. The DSR control strategies for major downstream network participants are designed and the benefits for customers and networks are quantified. In detail, the work in this thesis can be concluded as follows:

New problem formulations for optimal DSR customer benefits

Majority of previous DSR problem formulation either has large solution space that is complex to solve or oversimplify the optimization model for faster solution. This is because all previous DSR control problem formulations are designed on the component level that enumerates power exchange between components to model power flows among power sources and loads, such as battery, local system and main grid, with separate variables and constraints. The formulation would significantly increase the problem complexity as the problem size is linked exponentially with the size of

variables and constraints. This situation will exacerbate as low carbon components will expand in many fold in future low carbon homes. On the other hand, the simplified approach that uses a constant system efficiency under all system conditions is inaccurate to represent the realistic EMS model and thus reduce the customer benefits.

Aiming to address this challenge, a piecewise function problem formulation is proposed to maximize the customer electricity bill saving. This new formulation is built at the whole system level such that all power transfers within AC/DC system are represented by a piecewise function relationship. The AC power drawn from the main grid is represented as piecewise functions of battery storage charging/discharging power or local DC power in coordinate planes. Different from constant conversion efficiencies in the previous models, the critical power related efficiencies are built into the piecewise functions as different piecewise function slopes. Then the piecewise function is directly converted to mixed integer model that could solved by MILP. It reduces the solution space and simplifies the problem solving process because the variables and constraints in the optimization model are only related to number of segments in piecewise functions which will not increases with the increases of components. The MILP optimization would generate the optimal coordinate points that represent optimal battery storage charging/discharging power and relevant total AC power at each time set. Therefore, the proposed formulation significantly reduces complexity in optimization, and also extends modelling capability for converter efficiency. The efficacy of the formulation is demonstrated on practical systems.

In traditional AC system, the proposed DSR control strategy effectively reduces the energy bill by 22%. The demonstration result also implies: 1) The battery control strategies can be greatly affected by load profiles. 2) Larger benefit will be brought in daytime high demand customers using the battery and EMS given high price during the day. 3) The battery is less important in overnight high demand customers. 4) The increased battery charge rate could bring increased electricity bill savings. However, the incremental benefit will be reduced after reaching certain battery charge rate; 5) In order to make full use of the battery in shifting demand in the EMS system, the efficiencies should be set with the consideration of price differences.

In hybrid AC/DC system, the demonstration illustrates that the proposed piecewise function formulation could bring up to 68% cost saving on customer electricity bills.

The formulation could bring stable 3.5-5% demand shifting benefits through the year. The total cost saving in summer is higher than that in winter because of high PV output.

The results also expose that the accurate conversion efficiency modelling is an important factor to guarantee maximum customer benefits. Traditional formulation that linearizes the non-linear conversion efficiency sacrifices the accurate and optimal control strategy to largely reduce the optimization problem solving difficulty. The power related efficiency representation in piecewise function formulation is more capable to model the realistic converter efficiencies and thus increases the cost saving up to 24%.

Compared with traditional component level formulation, the proposed whole system level model provides at least half variable and constraints number reduced, up to three quarters solution space saving and produce better optimization results as the objective value of proposed problem reduces 3%-5% compared to traditional formulation.

Multi-functional EMS and DSR impact quantification for maximum network operators' benefits

- Multi-functional EMS with simulated and practical performance analysis

There was limited research to combine the benefits of both customers and network operators into DSR optimization model in downstream network. Majority of the previous DSR model is designed either for minimum customer electricity cost or minimum peak-to-average ratio. In the studies to minimum electricity cost, network peak demand reduction is achieved by synchronized high price and network peak demand. However, in LV network, where the demand are quite diverse and uncertain, the peak demand not always coincident with the peak demand of accumulated typical load profiles of customers. The DSR in the form of shared ownership battery is an improved option to bring benefit for both customers and network operators. The previous study on battery operation strategy are either unable to vary the battery capacity ownership during the day or to customize the DSR strategies for different customers on the same network.

Therefore, a new DSR optimization model for to maximize the customer benefits and

respond to network request during certain peak time is proposed. This new optimization model adds network power relief request into optimization formulation as constraints and therefore will primarily fulfil the network request for whole system benefits. Additionally, the study for the first time provides an insight into how the realistic DSR performance on network demand reduction and how the results are different from what would be expected in the simulation.

The simulation results show that the multi-functional EMS could bring £1134 LV network investment deferral with 4.3% EMS penetration given the practical network utilization of 42%. However, when the EMS penetration increases to 12.5%, the network investment deferral will be £3038. Further, when the network utilization grow to 85% in the future, the network investment deferral could reach £10832. The customers' benefit reduces in this multi-functional EMS because of the reduced battery capacity utilization. Apart from reducing their own demand using battery, customers would export extra power to support network peak demand reduction. The customers located at the network with peak demand coincident with peak energy price will save more electricity bill, as 12.55% in the test network. The customers located at the network with peak demand at non-peak price time could only save 3.75% in electricity bill.

However, in the practical network trial, the DSR increasing and decreasing demand performance cannot be identified on networks given the 10% penetration of EMS. It is clearly proved that the DSR can effectively reduce peak demand for households by demand shifting, but the LV network demand does not reflect the effect of demand reduction or increase as expected.

The invisible contribution from customers DSR to demand reduction at the network is caused by inherent uncertainty in network demand and relatively low DSR penetration. The demand uncertainties in network demand masks the demand reduction effect brought by DSR. For the purpose of meaningful demand reduction on network, the DSR penetration level should be sufficient to make a real impact.

- Quantify the DSR volume for meaningful network impact

There is inherent uncertainty in network demand. With this uncertainty involved, the

network demand can be located within a certain interval. After DSR employed, if network demand is higher than before, the demand reduction effect of DSR is offset. Thus, the household aggregating effect of network demand reduction may not be able to be transferred to the network level. Without considering network demand uncertainty in practice, the previous cumulating and normalizing approaches to quantify the DSR network demand reduction are not accurate to assess DSR performance.

Therefore, a quantitative analysis on meaningful demand reduction introduced by DSR on LV networks under realistic scenarios is provided. A probability-based quantification method is proposed to investigate the minimum required DSR penetration rate for meaningful network demand reduction considering the demand uncertainty. The actual network demand considering uncertainty is defined using average value and distribution in statistics. The facts that the demand reduction happens or not are defined by probability. Consequently, the meaningful network demand reduction is derived from a statistical calculation. In the quantification method, “divide-and-conquer” strategy, which is widely used in computer science, is adopted to find the minimum required DSR penetration and with reduced calculation complexity.

The demonstration conducted on the practical network used in the previous chapter shows that to guarantee network peak reduction at 95% confidence level, the minimum required DSR volume is only around 15-25% of network peak demand. However, to guarantee 100% confidence level, the minimum required DSR volume significantly increases 50% of network peak demand. The guaranteed amount of peak demand reduction proportionally increases with the increase of DSR volume at the each confidence level.

It is found that the amount of minimum required DSR volume is relatively stable over different months. However, the amount of minimum required DSR volume highly depends on network locations. It also implies the network demand uncertainty is relatively constant over time but significantly varies over locations.

DER management for optimal trading opportunities within local energy market

Currently, little research has investigated the DSR opportunities in the emerging new

market environment. The increasing unbalanced demand on the distribution network introduced by LCTs will trigger lots of local energy markets to digest the thermal and voltage violations locally and to offer capable customers access to energy markets. Majority of the researches are investigating either the big picture of local energy market, including market structure, participants' role and business opportunities or the strategies for aggregators and DSOs. However, little research has concentrated on the value of DSR, as a commodity, to local market formulations.

This research proposes a new MILP based DSR optimization model within the market environment that both central and local energy market exist. The proposed "Peer-to-Peer" model makes most profitable trading for customer after receiving the price information from both markets. The customers demand, generation, storage capacity, and several price signals, including sell and buy prices in both energy markets, are input into the optimization model. Different trading scenarios are transferred as 0-1 integer models and the optimal trading behaviours are derived from MILP. In the proposed market arrangement, customers could buy electricity from both central and local markets but could only sell electricity to local energy market. With different types of LCTs, customers could offer different electricity selling prices. At each trading period, each customer either bid or offer. The trading behaviours for different ask and accept prices scenarios for different types of customers are discussed in detail.

It is proved that, different from scenarios of customers with only distributed generation, the customers with battery have more trading flexibility and could freely choose the time and amount to trading in the markets. Therefore, in the local energy market, the customer with battery could play as a middleman, who buys electricity at low demand period with cheapest price from a PV-only holder or from a wind turbine only holder and sells it with increased price when demand is increased. The results show that the margin between the actual purchase cost and corresponding selling price has a substantial impact on the eventual profitability.

The customers with battery are not suitable to offer a "sunshine tariff" even they have PV in their homes. On the contrary, the customers with battery are suitable to accept the "sunshine tariff" from PV-only holder and to use battery to arbitrage by shifting the power and selling the electricity in another time. If the "wind tariff" is neither the highest nor the lowest price in the local energy market, it is suitable for customers with

battery. The customers with battery could take full advantage of long-time moderate and stable price to flexibly arbitrage in the local energy market. The moderate “wind tariff” could act as insurances to guarantee the benefit of customers with battery.

Compared with SME DSR activities, domestic customers tend to be more suitable for participating in a local energy market environment. For one thing, the domestic customer, whose demand peak time is different from PV output peak time, has shown more trading flexibility and feasibility than the school customer. At the same time, the domestic customer, whose demand is lower than that of school, has more trading flexibility and feasibility than the school customer.

8.2 Future work

8.2.1 Application of EMS formulation in solving three phase imbalances

The optimal EMS model proposed in this work proved to help reduce the network peak demand. However, extensive penetration of single phase connected home LCTs may cause serious phase imbalance problem in distribution networks. The three-phase connected school battery storage in Sola Bristol project proved that battery could help to balance the three-phase demand and voltage imbalance: battery charges on one phase for voltage reduce and discharges on another phase for voltage increases. However, in the project, the minor charging and discharging behaviours are spontaneous and induced by the large voltage differences between the two phases on the network. In the future, the EMS formulation could be improved to response to the imbalance and control the amount of charging and discharge power to mitigate imbalance to aimed level.

8.2.2 Improved formulation to cooperate several customers’ DSR across network

In the proposed work, DSR management in only one local system is considered. Since in the LV network structure type is relatively simple, i.e. radial type network, the network problem could be mitigated by cumulative and identical DSR contribution.

However, given more complex network configuration, and more complicated network problems, such as mitigating network three phase imbalances and reducing the renewable introduced uncertainties, diverse DSRs are required. Additionally, to optimize the scheduling of local energy generations, energy storages and controllable loads, either centralized or distributed decision maker/whole-system energy management system is necessary. The piecewise function formulation could be extended to a centralized whole-system EMS. In detail, firstly, it is to build the local network into individual piecewise function formulation. Then, build each local network piecewise function on network formulation. Finally, by taking each piecewise function as a variable set/matrix, it is to optimize the sum of multiple piecewise functions representing different local networks to find the final solutions.

Moreover, the whole system DSR control strategies should be incorporated with uncertainty models. As there are inherent uncertainties in the network demand, the optimization model should take consideration of uncertain data. Therefore, the piecewise formulation could be converted into the robust optimization to model the strategies and behaviours of several DSRs.

8.2.3 Improved DSR control for local energy trading

The proposed DSR control strategy in local energy market trading simply assumes the trading DSR product is electricity with different prices in different energy markets. However, with different sources of the local generated electricity, the electricity quality/supply reliability are different. The electricity from energy storage with EMS could be the most reliable electricity. However, the electricity production from PV and wind could largely rely on weather and therefore, the supply reliability varies with time and locations. Therefore, future work could take different quality-electricity into consideration and transfer the different quality information into signals that could be input into the DSR formulations. One of the solutions is to build electricity quality information into price information.

Additionally, DSR control strategies for different customers in local energy market could be extended into an equilibrium system. The objective of the DSR is not only to maximize the benefit of individual customers but also to achieve the objectives of 1) maximum total trading quantity; 2) minimum network peak-to-average ratio; and 3)

minimum energy cost in the whole local energy market scale.

Publications

C. Zhao; S. Dong; C. Gu; F. Li; Y. Song; N. P. Padhy, "New Problem Formulation for Optimal Demand Side Response in Hybrid AC/DC Systems," IEEE Transactions on Smart Grid, vol.PP, no.99, pp.1-1.

C. Zhao, S. Dong, F. Li and Y. Song, "Optimal home energy management system with mixed types of loads," in CSEE Journal of Power and Energy Systems, vol. 1, no. 4, pp. 29-37, Dec. 2015.

C. Zhao, H. Shi, R. Li and F. Li, "Demand side response performance assessment: An impact analysis of load profile accuracy on DSR performances," 2015 IEEE Power & Energy Society General Meeting, Denver, CO, 2015, pp. 1-5.

C. Zhao, C. Gu, and F. Li, "Classification of low voltage distribution networks based on fixed data", 2015 Cired, 23rd International Conference on Electricity Distribution, Lyon, 2015, pp.1-5.

C. Zhao, C. Gu, F. Li and M. Dale, "Understanding LV network voltage distribution-UK smart grid demonstration experience," 2015 IEEE Power & Energy Society Innovative Smart Grid Technologies Conference (ISGT), Washington, DC, 2015, pp. 1-5.

Reference

- [1] UNFCCC. *Kyoto Protocol: Essential Background*. Available: http://unfccc.int/essential_background/items/6031.php
- [2] E. Commission. *The 2020 Climate and Energy Package*. Available: http://ec.europa.eu/clima/policies/strategies/2020_en
- [3] S. o. S. f. E. a. C. Change, "Climate Change Act 2008," vol. 2014, ed, 2008.
- [4] Ofgem. (12.12/2016). *Electricity generation mix by quarter and fuel source (GB)*. Available: www.ofgem.gov.uk/chart/electricity-generation-mix-quarter-and-fuel-source-gb
- [5] H. Gharavi and R. Ghafurian, "Smart grid: The electric energy system of the future," 2011.
- [6] H. Farhangi, "The path of the smart grid," *IEEE power and energy magazine*, vol. 8, 2010.
- [7] U. S. E. P. Agency, "Energy Independence and Security Act of 2007 (EISA-2007)," ed: United States Environmental Protection Agency, 2007.
- [8] J. Momoh and J. A. Momoh, *Smart Grid Fundamentals of Design and Analysis*. Hoboken: Hoboken : Wiley, 2012.
- [9] D. Ofgem, Department of Energy and Climate Change, "Smart Grid Vision and Routemap," London2014.
- [10] Ofgem. (2015, 20 Nov). *RIIO-ED1 price control*. Available: <https://www.ofgem.gov.uk/network-regulation-riio-model/riio-ed1-price-control>
- [11] Ofgem. (2015, 20 Nov). *RIIO ED1 Financial Model (2.0 ed.)*. Available: <https://www.ofgem.gov.uk/network-regulation-riio-model/price-controls-financial-model-pcfm/riio-ed1-financial-model>
- [12] Ofgem. (12.2016). *Low carbon networks fund*. Available: <https://www.ofgem.gov.uk/electricity/distribution-networks/network-innovation/low-carbon-networks-fund>
- [13] C. Edge, "The UK smart meter installation programme: implementing strategic planning and optimised operational systems to get through the door," in *Asset Management Conference 2012, IET & IAM*, 2012, pp. 1-5.
- [14] E. I. S. Department for Business, "Smart meters: a guide," E. I. S. Department for Business, Ed., ed: Department for Business, Energy & Industrial Strategy, 2013.
- [15] Ofgem. (12.2016). *FIT tariff rates*. Available: <https://www.ofgem.gov.uk/environmental-programmes/fit/fit-tariff-rates>
- [16] E. I. S. Department for Business, "Digest of UK Energy Statistics (DUKES)," 28.07.2016 2016.
- [17] Ofgem. (12.2016). *Domestic Renewable Heat Incentive*. Available: <https://www.ofgem.gov.uk/environmental-programmes/domestic-rhi>
- [18] D. E. Environment, "IEA HPP Annex 42: heat pumps in Smart Grids," Delta Energy & Environment, UK2014.
- [19] C. Lilly. (7/01/2016, 12.2016). *Electric vehicle market statistics* Available: <http://www.nextgreencar.com/electric-cars/statistics/>
- [20] Ofgem, "Demand Side Response: A Discussion Paper," 2010.
- [21] N. Grid. (12.2016). *Demand side reponse*. Available: <http://www2.nationalgrid.com/UK/Services/Balancing-services/Demand-Side-Response/>

- [22] PJM. (12.2016). *Demand response*. Available: <http://www.pjm.com/markets-and-operations/demand-response.aspx>
- [23] K. Spees and L. Lave, "Impacts of responsive load in PJM: Load shifting and real time pricing," *Energy J.*, vol. 29, pp. 101-121, 2008.
- [24] J. Stede. (2016). *Demand response in Germany: Technical potential, benefits and regulatory challenges*. Available: https://www.diw.de/en/diw_01.c.532689.en/press/diw_roundup/demand_response_in_germany_technical_potential_benefits_and_regulatory_challenges.html
- [25] V. Lauber and S. Jacobsson, "The politics and economics of constructing, contesting and restricting socio-political space for renewables – The German Renewable Energy Act," *Environmental Innovation and Societal Transitions*, vol. 18, pp. 147-163, 3// 2016.
- [26] uSwitch. (12.2016). *What is Economy 7 meter and how does the tariff work?* Available: <https://www.uswitch.com/gas-electricity/guides/economy-7/>
- [27] D. o. E. C. Change, "UK Solar PV strategy part1: Roadmap to a brighter future," 2013.
- [28] E. I. S. Department for Business, "Digest of UK Energy Statistics ", E. I. S. Department for Business, Ed., ed. London: Department for Business, Energy & Industrial Strategy, 2017.
- [29] A. Goater, "Energy Storage," Houses of Parliament, Parliamentary office of science & technology2015.
- [30] E. A. G. G. Grimwood, "Commons Library analysis: Energy Storage in the UK," House of Parliament2016.
- [31] D. o. E. a. C. Change, "Draft Report on capturing the full electricity efficiency potential of the U.K.," 2012.
- [32] N. Powergrid. *Customer-Led Network Revolution*. Available: <http://www.networkrevolution.co.uk/>
- [33] D. H. P. Association, "Positioning paper: Heat pumps in domestic housing and demand management," 2015.
- [34] A. Safdarian, M. Fotuhi-Firuzabad, and M. Lehtonen, "Benefits of Demand Response on Operation of Distribution Networks: A Case Study," *IEEE Systems Journal*, vol. 10, pp. 189-197, 2016.
- [35] K. McKenna and A. Keane, "Residential Load Modeling of Price-Based Demand Response for Network Impact Studies," *IEEE Transactions on Smart Grid*, vol. 7, pp. 2285-2294, 2016.
- [36] N. Kinhekar, N. P. Padhy, F. Li, and H. O. Gupta, "Utility Oriented Demand Side Management Using Smart AC and Micro DC Grid Cooperative," *IEEE Transactions on Power Systems*, vol. 31, pp. 1151-1160, 2016.
- [37] D. Pudjianto, M. Aunedi, P. Djapic, and G. Strbac, "Whole-Systems Assessment of the Value of Energy Storage in Low-Carbon Electricity Systems," *Smart Grid, IEEE Transactions on*, vol. 5, pp. 1098-1109, 2014.
- [38] S. Beer, T. Gomez, D. Dallinger, I. Momber, C. Marnay, M. Stadler, *et al.*, "An Economic Analysis of Used Electric Vehicle Batteries Integrated Into Commercial Building Microgrids," *Smart Grid, IEEE Transactions on*, vol. 3, pp. 517-525, 2012.
- [39] H. Karami, M. J. Sanjari, S. H. Hosseini, and G. B. Gharehpetian, "An Optimal Dispatch Algorithm for Managing Residential Distributed Energy Resources," *Smart Grid, IEEE Transactions on*, vol. 5, pp. 2360-2367, 2014.

- [40] A. D. Peacock and M. Newborough, "Impact of micro-combined heat-and-power systems on energy flows in the UK electricity supply industry," *Energy*, vol. 31, pp. 1804-1818, 9// 2006.
- [41] A. D. Peacock and M. Newborough, "Effect of heat-saving measures on the CO₂ savings attributable to micro-combined heat and power (μ CHP) systems in UK dwellings," *Energy*, vol. 33, pp. 601-612, 4// 2008.
- [42] M. H. Albadi and E. F. El-Saadany, "Demand Response in Electricity Markets: An Overview," in *Power Engineering Society General Meeting, 2007. IEEE*, 2007, pp. 1-5.
- [43] B. Li, J. Shen, X. Wang, and C. Jiang, "From controllable loads to generalized demand-side resources: A review on developments of demand-side resources," *Renewable and Sustainable Energy Reviews*, vol. 53, pp. 936-944, 1// 2016.
- [44] EURELECTRIC, "Everything you always wanted to know about demand response," EURELECTRIC, Ed., ed. Brussels, Belgium: EURELECTRIC, 2015.
- [45] U. D. o. Energy, "Benefits of Demand Response in Electricity Markets and Recommendations for Achieving Them," 2006.
- [46] Elexon, "Load Profiles and their Use in Electricity settlement," ed: Elexon Ltd, 2012.
- [47] A. Faruqui and L. Wood, "Quantifying the benefits of dynamic pricing in the mass market," *Edison Electric Institute, Tech. Rep*, 2008.
- [48] W. Zhimin, "Smart Pricing for Smart Grid," PhD, The Department of Electronic and Electrical Engineering, University of Bath, UK, 2014.
- [49] T. H. a. J. Thumim, "An analysis of D3 in DECC's energy system models," Centre for Sustainable Energy 2014.
- [50] P. Boait, "Energy Services and ESCos – their benefits and implications for regulation and the consumer," 2009.
- [51] Elexon, "Encouraging local energy supply through a local balancing unit," Elexon.
- [52] F. Hvelplund, "Renewable energy and the need for local energy markets," *Energy*, vol. 31, pp. 2293-2302, 10// 2006.
- [53] Ofgem. (12.2016). *Electricity System Flexibility*. Available: <https://www.ofgem.gov.uk/electricity/retail-market/market-review-and-reform/smarter-markets-programme/electricity-system-flexibility>
- [54] G. O. Clare Dudeney, Judith Ward, "GB Electricity Demand Project-realising the resource," Sustainability First 2014.
- [55] E. I. S. Department for Business, "Opportunities for integrating demand side energy policies," Department for Business, Energy & Industrial Strategy July 2014 2014.
- [56] Ofgem, "Industrial & Commercial demand-side response in GB: barriers and potential," Ofgem 2016.
- [57] O. o. G. a. E. M. (OFGEM), "Electricity Storage Comparative Case Studies " Office of Gas and Electricity Markets (OFGEM) 2016.
- [58] U. o. C. Energy Policy Research Group. (2015, 12.2016). *Exploring the market for demand side response*. Available: <http://www.eprg.group.cam.ac.uk/wp-content/uploads/2016/05/O.Khalid.pdf>
- [59] W. P. Distribution. (2012, Nov 19). *So La Bristol*. Available: <http://www.westernpowerinnovation.co.uk/So-La-Bristol.aspx>
- [60] D. o. E. C. Change, "Future potential for Demand Side Response in Great Britain," 2015.

- [61] ENA, "Demand side response in the domestic sector-a literature review of major trials," ena2012.
- [62] T. S. Cambridge Economic Policy Associates Ltd, Imperial College London, "Demand side flexibility, The potential benefits and state of play in the European Union," Cambridge Economic Policy Associates Ltd, TPA Solutions, Imperial College London2014.
- [63] P. P. Doug Hurley, Melissa Whited, "Demand response as power system resource," Regulatory Assistance Project (RAP)2013.
- [64] U. Congress, "Energy policy act of 2005," *Public Law*, vol. 109, p. 42, 2005.
- [65] dena. (2015). *Marktentwicklung Lastmanagement in Deutschland (dena-Ergebnispapier)*. Deutsche Energie-Agentur. Available: http://www.effiziente-energiesysteme.de/fileadmin/user_upload/1_Fachmodule/Lastmanagement/15_0213_Ergebnispapier_Marktentwicklung.pdf>
- [66] M. Borup, "Electric mobility case study for Denmark," 2014.
- [67] P. Cappers, C. Goldman, and D. Kathan, "Demand response in US electricity markets: Empirical evidence," *Energy*, vol. 35, pp. 1526-1535, 2010.
- [68] X. Li and S. Hong, "User-expected price-based demand response algorithm for a home-to-grid system," *Energy*, vol. 64, pp. 437-449, 2014.
- [69] W. Zhimin, L. Furong, and L. Zhenjie, "Active household energy storage management in distribution networks to facilitate demand side response," in *Power and Energy Society General Meeting, 2012 IEEE*, 2012, pp. 1-6.
- [70] M. Rastegar, M. Fotuhi-Firuzabad, and F. Aminifar, "Load commitment in a smart home," *Applied Energy*, vol. 96, pp. 45-54, 8// 2012.
- [71] M. Pipattanasomporn, M. Kuzlu, and S. Rahman, "An Algorithm for Intelligent Home Energy Management and Demand Response Analysis," *Smart Grid, IEEE Transactions on*, vol. 3, pp. 2166-2173, 2012.
- [72] M. A. Pedrasa, T. D. Spooner, and I. F. MacGill, "Coordinated Scheduling of Residential Distributed Energy Resources to Optimize Smart Home Energy Services," *Smart Grid, IEEE Transactions on*, vol. 1, pp. 134-143, 2010.
- [73] Y. Riffonneau, S. Bacha, F. Barruel, and S. Ploix, "Optimal Power Flow Management for Grid Connected PV Systems With Batteries," *Sustainable Energy, IEEE Transactions on*, vol. 2, pp. 309-320, 2011.
- [74] W. Zhi, Z. Suyang, L. Jianing, and Z. Xiao-Ping, "Real-Time Scheduling of Residential Appliances via Conditional Risk-at-Value," *Smart Grid, IEEE Transactions on*, vol. 5, pp. 1282-1291, 2014.
- [75] G. Yuanxiong, P. Miao, and F. Yuguang, "Optimal Power Management of Residential Customers in the Smart Grid," *Parallel and Distributed Systems, IEEE Transactions on*, vol. 23, pp. 1593-1606, 2012.
- [76] Y. Ozturk, D. Senthilkumar, S. Kumar, and G. Lee, "An Intelligent Home Energy Management System to Improve Demand Response," *Smart Grid, IEEE Transactions on*, vol. 4, pp. 694-701, 2013.
- [77] J. Zhao, S. Kucuksari, E. Mazhari, and Y.-J. Son, "Integrated analysis of high-penetration PV and PHEV with energy storage and demand response," *Applied Energy*, vol. 112, pp. 35-51, 12// 2013.
- [78] O. Erdinc, N. G. Paterakis, T. D. P. Mendes, A. G. Bakirtzis, and J. P. S. Catalao, "Smart Household Operation Considering Bi-Directional EV and ESS Utilization by Real-Time Pricing-Based DR," *Smart Grid, IEEE Transactions on*, vol. 6, pp. 1281-1291, 2015.

- [79] F. Locment, M. Sechilariu, and I. Houssamo, "DC Load and Batteries Control Limitations for Photovoltaic Systems. Experimental Validation," *Power Electronics, IEEE Transactions on*, vol. 27, pp. 4030-4038, 2012.
- [80] E. Skoplaki and J. A. Palyvos, "On the temperature dependence of photovoltaic module electrical performance: A review of efficiency/power correlations," *Solar Energy*, vol. 83, pp. 614-624, 5// 2009.
- [81] S. H. Antonio Luque. (2005). *Handbook of Photovoltaic Science and Engineering*.
- [82] (2017). *4.8KWh Home Solar Panel Battery Storage System (Price Includes Home Installation)*. Available: <https://www.renewableenergyhub.co.uk/product/4-8kwh-home-solar-panel-battery-storage-system-price-includes-home-installation.html>
- [83] (2017). *1.5KW UBBINK/PERLIGHT SOLAR PV KIT - MCS ACCREDITED*. Available: http://www.buypvdirect.co.uk/1.5KW_Ubbink_Solar_PV_Kit
- [84] I. CLOVER. (2016). *IRENA forecasts 59% solar PV price reduction by 2025*. Available: https://www.pv-magazine.com/2016/06/15/irena-forecasts-59-solar-pv-price-reduction-by-2025_100024986/
- [85] F. Lambert. (2017). *Electric vehicle battery cost dropped 80% in 6 years down to \$227/kWh – Tesla claims to be below \$190/kWh*. Available: <https://electrek.co/2017/01/30/electric-vehicle-battery-cost-dropped-80-6-years-227kwh-tesla-190kwh/>
- [86] D. o. E. a. C. C. DECC, "The Carbon Plan: Delivering our low carbon future," D. o. E. a. C. Change, Ed., ed. London: Department of Energy and Climate Change, 2011.
- [87] J. Bird, "Developing the smarter grid: The role of domestic and small and medium enterprise customers," Northern Powergrid Plc, British Gas Trading Limited, EA Technology limited and University of Durham 2015.
- [88] A. Nottrott, J. Kleissl, and B. Washom, "Energy dispatch schedule optimization and cost benefit analysis for grid-connected, photovoltaic-battery storage systems," *Renewable Energy*, vol. 55, pp. 230-240, 7// 2013.
- [89] L. Bo and M. Shahidehpour, "Short-term scheduling of battery in a grid-connected PV/battery system," *Power Systems, IEEE Transactions on*, vol. 20, pp. 1053-1061, 2005.
- [90] C. Chen, s. duan, T. Cai, B. Liu, and G. Hu, "Smart energy management system for optimal microgrid economic operation," *Renewable Power Generation, IET*, vol. 5, pp. 258-267, 2011.
- [91] H. Beltran, E. Bilbao, E. Belenguer, I. Etxeberria-Otadui, and P. Rodriguez, "Evaluation of Storage Energy Requirements for Constant Production in PV Power Plants," *Industrial Electronics, IEEE Transactions on*, vol. 60, pp. 1225-1234, 2013.
- [92] A. K. Barnes, J. C. Balda, and A. Escobar-Mejia, "A Semi-Markov Model for Control of Energy Storage in Utility Grids and Microgrids With PV Generation," *Sustainable Energy, IEEE Transactions on*, vol. 6, pp. 546-556, 2015.
- [93] P. Malysz, S. Sirouspour, and A. Emadi, "An Optimal Energy Storage Control Strategy for Grid-connected Microgrids," *Smart Grid, IEEE Transactions on*, vol. 5, pp. 1785-1796, 2014.
- [94] C. Yijia, T. Shengwei, L. Canbing, Z. Peng, T. Yi, Z. Zhikun, *et al.*, "An Optimized EV Charging Model Considering TOU Price and SOC Curve," *Smart Grid, IEEE Transactions on*, vol. 3, pp. 388-393, 2012.

- [95] J. Soares, H. Morais, T. Sousa, Z. Vale, and P. Faria, "Day-Ahead Resource Scheduling Including Demand Response for Electric Vehicles," *Smart Grid, IEEE Transactions on*, vol. 4, pp. 596-605, 2013.
- [96] H. Mohsenian-Rad and A. Davoudi, "Towards Building an Optimal Demand Response Framework for DC Distribution Networks," *Smart Grid, IEEE Transactions on*, vol. 5, pp. 2626-2634, 2014.
- [97] G. Byeon, T. Yoon, S. Oh, and G. Jang, "Energy Management Strategy of the DC Distribution System in Buildings Using the EV Service Model," *Power Electronics, IEEE Transactions on*, vol. 28, pp. 1544-1554, 2013.
- [98] W. Chengshan, L. Xialin, G. Li, and L. Yun Wei, "A Nonlinear-Disturbance-Observer-Based DC-Bus Voltage Control for a Hybrid AC/DC Microgrid," *Power Electronics, IEEE Transactions on*, vol. 29, pp. 6162-6177, 2014.
- [99] L. Xiong, W. Peng, and L. Poh Chiang, "A Hybrid AC/DC Microgrid and Its Coordination Control," *Smart Grid, IEEE Transactions on*, vol. 2, pp. 278-286, 2011.
- [100] M. Farhadi and O. Mohammed, "Adaptive Energy Management in Redundant Hybrid DC Microgrid for Pulse Load Mitigation," *Smart Grid, IEEE Transactions on*, vol. 6, pp. 54-62, 2015.
- [101] P. T. Baboli, M. Shahparasti, M. P. Moghaddam, M. R. Haghifam, and M. Mohamadian, "Energy management and operation modelling of hybrid AC–DC microgrid," *Generation, Transmission & Distribution, IET*, vol. 8, pp. 1700-1711, 2014.
- [102] A. Joseph and M. Shahidehpour, "Battery storage systems in electric power systems," in *2006 IEEE Power Engineering Society General Meeting*, 2006, p. 8 pp.
- [103] A. Y. S. Lam, L. Yiu-Wing, and C. Xiaowen, "Electric Vehicle Charging Station Placement: Formulation, Complexity, and Solutions," *Smart Grid, IEEE Transactions on*, vol. 5, pp. 2846-2856, 2014.
- [104] J. Chenrui, T. Jian, and P. Ghosh, "Optimizing Electric Vehicle Charging With Energy Storage in the Electricity Market," *Smart Grid, IEEE Transactions on*, vol. 4, pp. 311-320, 2013.
- [105] J. W. Chinneck, "Practical optimization: a gentle introduction," *Systems and Computer Engineering*, Carleton University, Ottawa. <http://www.sce.carleton.ca/faculty/chinneck/po.html>, 2006.
- [106] Z. W. Ran Li, Simon Le Blond, Furong Li, "Development of Time-of-Use Price by Clustering Techniques," presented at the Power and Energy Society General Meeting, Washington, D.C., 2014.
- [107] S. B. Kjaer, J. K. Pedersen, and F. Blaabjerg, "A review of single-phase grid-connected inverters for photovoltaic modules," *Industry Applications, IEEE Transactions on*, vol. 41, pp. 1292-1306, 2005.
- [108] R. L.-H. John Forrest, "CBC User Guide," ed, 2005.
- [109] D. o. E. a. C. C. McKinsey & Co; DECC, "Capturing the full electricity efficiency potential of the UK," D. o. E. a. C. C. DECC, Ed., ed, 2012, p. 129.
- [110] L. Meng, F. Quilumba, and L. WeiJen, "A Collaborative Design of Aggregated Residential Appliances and Renewable Energy for Demand Response Participation," *Industry Applications, IEEE Transactions on*, vol. 51, pp. 3561-3569, 2015.
- [111] M. Shinwari, A. Youssef, and W. Hamouda, "A Water-Filling Based Scheduling Algorithm for the Smart Grid," *Smart Grid, IEEE Transactions on*, vol. 3, pp. 710-719, 2012.

- [112] C. Ibars, M. Navarro, and L. Giupponi, "Distributed Demand Management in Smart Grid with a Congestion Game," in *Smart Grid Communications (SmartGridComm), 2010 First IEEE International Conference on*, 2010, pp. 495-500.
- [113] S. Wenbo, L. Na, X. Xiaorong, C. Chi-Cheng, and R. Gadh, "Optimal Residential Demand Response in Distribution Networks," *Selected Areas in Communications, IEEE Journal on*, vol. 32, pp. 1441-1450, 2014.
- [114] Z. Wang, C. Gu, F. Li, P. Bale, and H. Sun, "Active Demand Response Using Shared Energy Storage for Household Energy Management," *IEEE Transactions on Smart Grid*, vol. 4, pp. 1888-1897, 2013.
- [115] N. Hung Khanh, J. B. Song, and H. Zhu, "Demand side management to reduce Peak-to-Average Ratio using game theory in smart grid," in *Computer Communications Workshops (INFOCOM WKSHPS), 2012 IEEE Conference on*, 2012, pp. 91-96.
- [116] M. Cresta, F. M. Gatta, A. Geri, M. Maccioni, A. Mantineo, and M. Paulucci, "Optimal operation of a low-voltage distribution network with renewable distributed generation by NaS battery and demand response strategy: a case study in a trial site," *Renewable Power Generation, IET*, vol. 9, pp. 549-556, 2015.
- [117] T. Zhao, Y. Peng, and A. Nehorai, "An Optimal and Distributed Demand Response Strategy With Electric Vehicles in the Smart Grid," *Smart Grid, IEEE Transactions on*, vol. 5, pp. 861-869, 2014.
- [118] A. Mnatsakanyan and S. W. Kennedy, "A Novel Demand Response Model with an Application for a Virtual Power Plant," *Smart Grid, IEEE Transactions on*, vol. 6, pp. 230-237, 2015.
- [119] A. Poghosyan, D. V. Greetham, S. Haben, and T. Lee, "Long term individual load forecast under different electrical vehicles uptake scenarios," *Applied Energy*, vol. 157, pp. 699-709, 2015.
- [120] Z. Wang, Q. Lihan, C. Gu, and F. Li, "Distributed storage capacity reservations for residential PV generation utilization and LV network operation," in *2015 IEEE Power & Energy Society General Meeting*, 2015, pp. 1-5.
- [121] Z. Chen, S. Heng, L. Ran, and L. Furong, "Demand side response performance assessment: An impact analysis of load profile accuracy on DSR performances," in *2015 IEEE Power & Energy Society General Meeting*, 2015, pp. 1-5.
- [122] P. Bale, "Low Carbon Network Fund Successful Delivery Reward Criteria: 9.2 - Confirmation of the SoLa BRISTOL design ", W. P. Distribution, Ed., ed, 2012.
- [123] L. Furong and D. L. Tolley, "Long-Run Incremental Cost Pricing Based on Unused Capacity," *Power Systems, IEEE Transactions on*, vol. 22, pp. 1683-1689, 2007.
- [124] W. P. Distribution. (2014). *CDMC-ARP-April-2015-Pre-Release-South-West-v2*. Available: <http://www.westernpower.co.uk/docs/system-charges/CDMC-Annual-Review-Pack/2015/CDMC-ARP-April-2015-Pre-Release-South-West-v2.aspx>
- [125] "Electricity Distribution Price Control Review Final Proposals - Allowed revenue - Cost assessment appendix ", O. o. G. a. E. Markets, Ed., ed. London, U.K.: Office of Gas and Electricity Markets 2009.

- [126] Z. Chen, S. Heng, L. Ran, and L. Furong, "Demand side response performance assessment: An impact analysis of load profile accuracy on DSR performances," in *Power & Energy Society General Meeting, 2015 IEEE*, 2015, pp. 1-5.
- [127] G. F. Simmons, *Topology and modern analysis* vol. 3: McGraw-Hill New York, 1963.
- [128] R. Engelking, "General topology," 1989.
- [129] P. Westacott and C. Candelise, "Assessing the impacts of photovoltaic penetration across an entire low-voltage distribution network containing 1.5 million customers," *IET Renewable Power Generation*, vol. 10, pp. 460-466, 2016.
- [130] G. Gutiérrez-Alcaraz, J. H. Tovar-Hernández, and C.-N. Lu, "Effects of demand response programs on distribution system operation," *International Journal of Electrical Power & Energy Systems*, vol. 74, pp. 230-237, 1// 2016.
- [131] W. Chi-Keung, I. Horowitz, and I. M. Sulyma, "Relative kW Response to Residential Time-Varying Pricing in British Columbia," *Smart Grid, IEEE Transactions on*, vol. 4, pp. 1852-1860, 2013.
- [132] D. Crow, "Divide and Conquer," *Scientific American*, vol. 315, pp. 14-15, 2016.
- [133] H. Verbeek, W. van der Aalst, and J. Munoz-Gama, "Divide and Conquer," Technical report, BPM Center Report Series 2016.
- [134] A. Leon-Garcia, "Probability and Random Processes," *Addison Wesley, Table*, vol. 3, pp. 126-127, 1989.
- [135] W. H. Beyer, *Standard Probability and Statistics: Tables and Formulae*: CRC Press, 1991.
- [136] T. H. Cormen, *Introduction to algorithms*: MIT press, 2009.
- [137] J. C. Clive Tomlinson, Anthony Price, Joe Handford, "Community Energy Markets," Swabbarton, IPL 2013.
- [138] A. Jalia, N. Honeth, C. Sandels, and L. Nordstrom, "A Local Market Model for Urban Residential Microgrids with Distributed Energy Resources," in *2012 45th Hawaii International Conference on System Sciences*, 2012, pp. 1949-1958.
- [139] D. Ilic, P. G. D. Silva, S. Karnouskos, and M. Griesemer, "An energy market for trading electricity in smart grid neighbourhoods," in *2012 6th IEEE International Conference on Digital Ecosystems and Technologies (DEST)*, 2012, pp. 1-6.
- [140] M. Ampatzis, P. H. Nguyen, and W. Kling, "Local electricity market design for the coordination of distributed energy resources at district level," in *IEEE PES Innovative Smart Grid Technologies, Europe*, 2014, pp. 1-6.
- [141] A. H. Mohsenian-Rad, V. W. S. Wong, J. Jatskevich, R. Schober, and A. Leon-Garcia, "Autonomous Demand-Side Management Based on Game-Theoretic Energy Consumption Scheduling for the Future Smart Grid," *IEEE Transactions on Smart Grid*, vol. 1, pp. 320-331, 2010.
- [142] K. Ma, G. Hu, and C. J. Spanos, "Energy consumption scheduling in smart grid: A non-cooperative game approach," in *2013 9th Asian Control Conference (ASCC)*, 2013, pp. 1-6.
- [143] M. P. F. Hommelberg, C. J. Warmer, I. G. Kamphuis, J. K. Kok, and G. J. Schaeffer, "Distributed Control Concepts using Multi-Agent technology and Automatic Markets: An indispensable feature of smart power grids," in *2007 IEEE Power Engineering Society General Meeting*, 2007, pp. 1-7.

- [144] N. Capodiecici, G. Cabri, G. A. Pagani, and M. Aiello, "An Agent-Based Application to Enable Deregulated Energy Markets," in *2012 IEEE 36th Annual Computer Software and Applications Conference*, 2012, pp. 638-647.
- [145] Y. Wu, X. Tan, L. Qian, D. H. K. Tsang, W. Z. Song, and L. Yu, "Optimal Pricing and Energy Scheduling for Hybrid Energy Trading Market in Future Smart Grid," *IEEE Transactions on Industrial Informatics*, vol. 11, pp. 1585-1596, 2015.
- [146] S. S. Torbaghan, N. Blaauwbroek, P. Nguyen, and M. Gibescu, "Local market framework for exploiting flexibility from the end users," in *2016 13th International Conference on the European Energy Market (EEM)*, 2016, pp. 1-6.
- [147] D. J. MacKay, "Sustainable Energy—without the hot air," *UIT Cambridge, England*, 2009.
- [148] E. Vine, "An international survey of the energy service company (ESCO) industry," *Energy Policy*, vol. 33, pp. 691-704, 2005.
- [149] S. Parsons, M. Marcinkiewicz, J. Niu, and S. Phelps, "Everything you wanted to know about double auctions, but were afraid to (bid or) ask," *City University of New York: New York 2005*, 2006.
- [150] D. Papadaskalopoulos, G. Strbac, P. Mancarella, M. Aunedi, and V. Stanojevic, "Decentralized Participation of Flexible Demand in Electricity Markets—Part II: Application With Electric Vehicles and Heat Pump Systems," *Power Systems, IEEE Transactions on*, vol. 28, pp. 3667-3674, 2013.
- [151] T. Masuta and A. Yokoyama, "Supplementary Load Frequency Control by Use of a Number of Both Electric Vehicles and Heat Pump Water Heaters," *Smart Grid, IEEE Transactions on*, vol. 3, pp. 1253-1262, 2012.
- [152] C. Vuillecard, C. E. Hubert, R. Contreau, A. Mazzenga, P. Stabat, and J. Adnot, "Small scale impact of gas technologies on electric load management - mu CHP & hybrid heat pump," *Energy*, vol. 36, pp. 2912-2923, May 2011.
- [153] M. Houwing, R. R. Negenborn, and B. De Schutter, "Demand Response With Micro-CHP Systems," *Proceedings of the Ieee*, vol. 99, pp. 200-213, Jan 2011.
- [154] D. f. B. E. a. R. R. D. f. Transport. (2008, February). *Investigation into the scope for the transport sector to switch to electric vehicles and plug-in hybrid vehicles*.
- [155] P. Papadopoulos, S. Skarvelis-Kazakos, I. Grau, L. M. Cipcigan, and N. Jenkins, "Electric vehicles' impact on british distribution networks," *Electrical Systems in Transportation, IET*, vol. 2, pp. 91-102, 2012.
- [156] I. E. A. (IEA), "Global EV Outlook 2016," International Energy Agency (IEA), France 2016.
- [157] A. Pyrgou, A. Kylili, and P. A. Fokaides, "The future of the Feed-in Tariff (FiT) scheme in Europe: The case of photovoltaics," *Energy Policy*, vol. 95, pp. 94-102, 8// 2016.
- [158] W. R. E. N. W. Western Power Distribution, Tempus Energy, Regen SW. (2015, 12.2016). *Sunshine Tariff*. Available: [https://www.westernpowerinnovation.co.uk/Projects/Current-Projects/Sunshine-Tariff.aspx#FAQLink76;javascript:void\(0\);](https://www.westernpowerinnovation.co.uk/Projects/Current-Projects/Sunshine-Tariff.aspx#FAQLink76;javascript:void(0);)